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*"Gheorghe Asachi" Technical University of Iasi, Romania*

# SPATIAL ECONOMETRICS ANALYSIS ON THE CONVERGENCE OF LOW-CARBON ECONOMIC GROWTH EFFICIENCY IN THE YANGTZE RIVER ECONOMIC BELT

**Hualei Ju[1], Xiaheng Zhang[2*]**

[1]*School of Economics, Northwest University of Political Science and Law, Xi'an 710122, China*
[2]*Business School, Northwest University of Political Science and Law, Xi'an 710122, China*

**Abstract**

Based on the panel data of the Yangtze River Economic Belt in 1998-2016, this paper carries out a spatial econometrics analysis on the convergence of low-carbon economic growth efficiency (LCEGE) in the Belt. The main results are as follows: there are huge provincial differences in the LCEGE across the Belt; the spatial autocorrelation (Global Moran's I) test shows a significant spatial correlation of the LCEGE, with an obvious regional spatial clustering effect; considering the spatial effects, the provincial gap in the LCEGE is reduced gradually at an absolute convergence rate of 5.85%; the LCEGE has a significant positive correlation with the R&D investment and opening-up, a significant negative correlation with industrial structure and energy structure, and an insignificant correlation with environmental regulation.

*Keywords:* convergence analysis, low-carbon economic growth efficiency (LCEGE), spatial econometrics, Yangtze River Economic Belt

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## 1. Introduction

The Yangtze River Economic Belt, covering an area of 2.0523 million $km^2$, is the key to China's Belt and Road Initiative. There are 11 provincial-level administrative regions in the Belt, namely, Shanghai, Jiangsu, Zhejiang, Anhui, Jiangxi, Hubei, Hunan, Chongqing, Sichuan, Yunnan and Guizhou. In 2014, the Chinese State Council released *the Guiding Opinions on Promoting the Development of the Yangtze River Economic Belt by Utilizing the Golden Waterway*, which promises to turn the Belt into an eco-economic demonstration zone for green recycling and low-carbon development.

With only 21.4% of China's territorial area, the Yangtze River Economic Belt feeds more than 40% of the Chinese population and contributes more than 40% to the country's GDP. However, the Belt takes up an even greater proportion (45%) in terms of total carbon emissions. To rensure the sustainable development, the Belt must shift its economic mode from high-carbon growth to low-carbon development. The modal shift is in line with the national goal to reduce the carbon emission intensity per unit of GDP by 40%~45% in 2020. To promote the modal shift, the following questions must be answered: what is the current situation of the modal shift towards low-carbon economy in the Belt? Are there significant differences in the low-carbon economic growth efficiency (LCEGE) between the upper, middle and lower reaches? Is it possible to achieve balanced and joint development?

The modal shift in the Yangtze River Economic Belt has attracted growing attentions in the academia. The existing studies mainly concentrate on the current situation of carbon emissions and the

[*]Author to whom all correspondence should be addressed: e-mail: zhangxiaheng@163.com; Phone: 02988182575

efficiency of emission reduction (Tu and Ma, 2018; Zhang et al., 2018). For example, Huang et al. (2016) analyzed the current status and the influencing factors of carbon emissions in the Belt, and attributed the continuous growth of carbon emissions in the Belt to economy, population and energy. Tian et al. (2016) evaluated the emission reduction efficiency of the Belt by data envelopment analysis (DEA), and designed a path for the low-carbon economic transformation of the Belt. Zhang (2018) explored the low-carbon, coordinated development of the Belt through multiplier decomposition, and concluded that the development mode can be effectively stimulated by expanding domestic demand, adjusting the structure of foreign trade and optimizing the structure of energy consumption. From the low-carbon perspective, Cao and Zeng (2019) introduced a super slack-based model (SBM) with agricultural carbon sink as desired output, and agricultural carbon emissions as undesired output, and used the super SBM to measure the agricultural ecological efficiency in the Belt. Using the panel data model of the Belt, Shi and Tang (2019) set up an index of low-carbon technical innovation and decomposed carbon emissions, before investigating the effects of low-carbon technical innovation on carbon emissions and the response of energy consumption to low-carbon technology. Yuan and Tang (2019) interpreted the data on the images on the Belt captured by Landsat 4 Thematic Mapper (TM) in 2000-2015, and constructed a carbon emissions model to examine the spatial heterogeneity of land use carbon emissions based on economic contribution, eco-carrying ability and the coupling relationship between the two factors.

Despite the above results, the existing studies on the modal shift in the Belt face two common defects. First, the carbon sink effect of afforestation is not considered in the index system for the LCEGE evaluation, leading to evaluation errors. Second, the spatial spillover across different regions is ignored in the cause analysis on the provincial differences in the LCEGE, i.e. each province is treated as an independent spatial unit. In fact, the interregional spatial spillover is confirmed by Tobler (1979) in his first law of geography: "everything is related to everything else, but near things are more related than distant things". To overcome the two defects, this paper introduces the carbon sink factor to the LCEGE evaluation system, and then evaluates the status of modal shift to low-carbon economy in the Yangtze River Economic Belt by the minimum distance to the strongest efficient frontier (MDSEF) method. After that, the LCEGE convergence in the Belt was investigated by spatial econometric method, and the main driving factors of the regional difference in low-carbon economy were identified.

## 2. Research method and empirical model

### 2.1. The MDSEF method

Inspired by the improved DEA of Jahanshahloo et al. (2012), this paper puts forward the MDSEF method with an undesired output. This method measures the optimal efficiency of the object in three steps: set up a production set, screen all projection points on the set, and identify the projection point with the minimum distance to the frontier.

Suppose there is a complete production set of input and output variables, involving n DMUs. Let *m* be the number of production factors required for each DMU, and *s1* and *s2* be the desired and undesired unit outputs, respectively. For convenience, the input factors, desired outputs and undesired outputs are expressed as vectors $X=(x_1,x_2,...,x_n)\in R_+^{m\times n}$, $Y_g=(y_1^g,y_2^g,...,y_n^g)\in R_+^{s_1\times n}$, $Y_b=(y_1^b,y_2^b,...,y_n^b)\in R_+^{s_2\times n}$, respectively.

Assuming that $P^t(x)=\{(x,y): x\ can\ product\ y\}$ is the entire set of possible products and $DMU_0=(x_0,y_0^g,y_0^b)$ is the decision-making system in the production process, all the output units in the production set that represent the strongest efficient frontier can be characterized as $F^s(P)$. Then, the projection point with the minimum distance $L_1$to the frontier can be identified from the production set. On this basis, the MDSEF method can be modelled as given by Eqs. (1, 2):

$$
\begin{aligned}
(mSBM)\quad & \min\Big(\sum_{i=1}^{m}s_{i0}^{-}+\sum_{r=1}^{s_1}s_{r0}^{+}+\sum_{l=1}^{s_2}s_{l0}^{-}\Big)+M\Big(\sum_{i=1}^{m}\overline{s}_{i0}^{-}+\sum_{r=1}^{s_1}\overline{s}_{r0}^{+}+\sum_{l=1}^{s_2}\overline{s}_{l0}^{-}\Big)\\
& s_{i0}^{-}\geq 0,\ i=1,...,m\\
& s_{r0}^{+}\geq 0,\ r=1,...,s_1\\
& s_{l0}^{-}\geq 0,\ l=1,...,s_2
\end{aligned}
\tag{1}
$$

$$
\begin{aligned}
& \max\Big(\sum_{i=1}^{m}\overline{s}_{i0}^{-}+\sum_{r=1}^{s_1}\overline{s}_{r0}^{+}+\sum_{l=1}^{s_2}\overline{s}_{l0}^{-}\Big)\\
s.t.\quad & \sum_{j\in E_c}\lambda_j x_{ij}+\overline{s}_{i0}^{-}=x_{i0}-s_{i0}^{-}\\
& \sum_{j\in E_c}\lambda_j y_{ij}^{g}-\overline{s}_{r0}^{+}=y_{i0}^{g}+s_{r0}^{+}\\
& \sum_{j\in E_c}\lambda_j y_{ij}^{b}+\overline{s}_{l0}^{-}=y_{i0}^{b}-s_{l0}^{-}\\
& \lambda_j\geq 0,\overline{s}_{i0}^{-}\geq 0,\overline{s}_{r0}^{+}\geq 0,\overline{s}_{l0}^{-}\geq 0
\end{aligned}
\tag{2}
$$

In Eq. (1), $s_{i0}^{-},s_{r0}^{+},\overline{s}_{l0}^{-},\overline{s}_{i0}^{-},\overline{s}_{r0}^{+},\overline{s}_{l0}^{-}$ are the relaxation terms reflecting the allowable change interval of the input and output variables during efficiency improvement; *m* is a constant term, which is usually a large positive number. Eq. (2) lists the constraints and highlights the bounded features of the model. Together, the two equations constitute a typical two-layer linear programming structure. As a modified version of the traditional SBM, the above model is denoted as mSBM. To turn the mSBM into an SBM, Eq. (2) of the mSBM can be rewritten as a linear constraint:

$$
\min\left(\frac{1-\frac{1}{m}\sum_{i=1}^{m}\overline{s}_{i0}^{-}/x_{i0}}{1+\frac{1}{s_1+s_2}\Big(\sum_{r=1}^{s_1}\overline{s}_{r0}^{+}/y_{r0}+\sum_{l=1}^{s_2}\overline{s}_{l0}^{-}/b_{l0}\Big)}\right)
\tag{3}
$$

The SBM is valid only if three equations $\sum_{i=1}^{m}\overline{s_{i0}^{-}}/x_{i0}, \sum_{r=1}^{s_1}\overline{s_{r0}^{+}}/y_{r0}$ and $\sum_{l=1}^{s_2}\overline{s_{l0}^{-}}/b_{l0}$, reach the maximum values. These equations exist in the form of fractions, where the denominators are constants and the numerators are relaxation terms (e.g. $\overline{s_{i0}^{-}},\overline{s_{r0}^{+}},\overline{s_{l0}^{-}}$). The SBM cannot measure the efficiency, unless the relaxation terms are maximized, i.e. the result of Eq. (3) is minimized. Thus, the SBM and mSBM have completely opposite constraints. The mSBM enjoys a huge advantage over the SBM in that the relaxation terms change slightly during efficiency improvement. During the efficiency evaluation of an economic activity, if the resources can be optimized with the minimal variable cost, the production decision-maker is more likely to make the optimal economic decisions.

### 2.2. Spatial autocorrelation coefficient

Spatial autocorrelation analysis on the measured data is a necessary step to verify the existence of provincial spatial spillover of the LCEGE in the Belt. The common indices of spatial autocorrelation include Moran's I and Geary's C. The former is more universal and practical than the latter. Therefore, this paper selects the Global Moran's I was selected to measure the spatial autocorrelation (Moran, 1948) (Eq. 4):

$$Moran's\ I = \frac{n}{\sum_{i=1}^{n}(x_i-\bar{x})^2}\frac{\sum_{i=1}^{n}\sum_{j=1}^{n}W_{ij}(x_i-\bar{x})(x_j-\bar{x})}{\sum_{i=1}^{n}\sum_{j=1}^{n}W_{ij}} \tag{4}$$

where, $n$ is the number of spatial units formed by all the objects; $x_i$ and $x_j$ are the observed values of regions $i$ and $j$, respectively; $\bar{x}=(\sum ix_i)/n$ is the mean observed value of all regions; $W_{ij}$ is the weight matrix between different regions. In general, the mean value measured by the Global Moran's I falls between -1 and 1. The weight matrix may exist as economic matrix, distance matrix or adjacency matrix. The adjacency matrix stands out for its simple and fast calculation and strong adaptability. Hence, this paper adopts the spatial adjacency weight matrix (Eq. 5):

$$W_{ij}=\begin{cases}1 & \text{Region i is adjacent to region j}\\ 0 & \text{Region i is not adjacent to region j}\end{cases} \tag{5}$$

To ensure its authenticity, the Moran's I value of the object should pass the significance test. The common test method is the Z-score table normal distribution. The Moran's I value is authentic if its Z-score can pass the tests on the significance of 1%, 5% and 10%. The Z-score table normal distribution can be expressed as Eq. (6):

$$Z(d)=\frac{[Moran's\ I - E(Moran's\ I)]}{\sqrt{VAR(Moran's\ I)}} \tag{6}$$

### 2.3. Beta-convergence panel model

*(1) Traditional beta-convergence model*

Baumol (1986) proposed the traditional convergence theory in the study of the difference in national income. The theory holds that, the regional income gap will gradually shrink with the elapse of time, i.e. the income of residents in backward areas will gradually catch up with that of residents in developed regions. There are two forms of convergence: the absolute beta-convergence and the conditional beta-convergence. The former refers to the natural convergence between the regions over time, without considering the impacts of external factors; the latter refers to the convergence between the regions, after considering the control variables. The absolute beta-convergence is defined as Eq. (7):

$$\frac{1}{T}\ln(\frac{y_{i,t+T}}{y_{i,t}}) = \alpha + \beta\ln(y_{i,t}) + \varepsilon_{i,t} \quad \varepsilon\sim N(0,\sigma^2) \tag{7}$$

where, $y_{i,t+T}$ and $y_{i,t}$are the economic output levels of region $i$ at time t and time t+T, respectively; α is a constant term; $\beta$=-(1-$e^{-\theta T}$), with $\theta$ being the convergence rate in the sample period. If $\beta$ is significantly negative, then the object must have exhibited the absolute convergence trend in the sample period. In other words, the output of backward regions increases much faster than that of developed regions, and the regional economic gap gradually narrows.

The conditional beta-convergence model can be constructed based on the absolute beta-convergence model. Introducing the control variables into Eq. 7, the conditional beta-convergence can be described as Eq. (8):

$$\frac{1}{T}\ln(\frac{y_{i,t+T}}{y_{i,t}}) = \alpha + \beta_1\ln(y_{i,t}) + \delta X_{i,t} + \varepsilon_{i,t} \quad \varepsilon\sim N(0,\sigma^2) \tag{8}$$

*(2) Spatial panel model of beta-convergence*

The traditional beta-convergence model assumes that the regions are completely independent of each other which clearly contradict the actual situation. The traditional model always has an error in measuring the convergence rate. To solve the problem, the spatial effect factors were introduced to modify the traditional beta-convergence model into the spatial panel model for the beta-convergence. According to the theory of spatial econometrics theory, the spatial autoregressive (SAR) model was integrated with the traditional convergence model to form the absolute beta-convergence model (Eq. 9) and conditional beta-convergence model (Eq. 10):

$$\frac{1}{T}\ln(\frac{y_{i,t+T}}{y_{i,t}}) = \alpha + \beta\ln(y_{i,t}) + \rho W\ln(\frac{y_{i,t+T}}{y_{i,t}}) + \varepsilon_{i,t} \quad \varepsilon\sim N(0,\sigma^2) \tag{9}$$

$$\frac{1}{T}\ln(\frac{y_{i,t+T}}{y_{i,t}}) = \alpha + \beta_1\ln(y_{i,t}) + \delta X_{i,t} + \rho W\ln(\frac{y_{i,t+T}}{y_{i,t}}) + \varepsilon_{i,t} \quad \varepsilon\sim N(0,\sigma^2) \tag{10}$$

where, ρ is the spatial autoregressive coefficient reflecting the magnitude of the spatial effects; *W* is the spatial weight matrix to be included in model operation; ε is a random error term.

After combining the spatial error model (SEM) and the traditional convergence model, the absolute beta-convergence model and conditional beta-convergence model can be expressed as Eqs. (11-12):

$$\frac{1}{T}\ln\left(\frac{y_{i,t+T}}{y_{i,t}}\right) = \alpha + \beta\ln(y_{i,t}) + \varepsilon_{i,t} \quad \varepsilon_{i,t} = \lambda W + u, u \sim N(0,\sigma^2 I) \tag{11}$$

$$\frac{1}{T}\ln\left(\frac{y_{i,t+T}}{y_{i,t}}\right) = \alpha + \beta_1\ln(y_{i,t}) + \delta X_{i,t} + \varepsilon_{i,t} \quad \varepsilon_{i,t} = \lambda W + u, u \sim N(0,\sigma^2 I) \tag{12}$$

where, λ the spatial error coefficient representing the spatial error of the residual term; *u* is the random disturbance term.

## 3. Index selection and data sources

### *3.1. Selection of input and output variables*

According to Lei and Yu (2015), the carbon sink factor is included in the carbon cycle total factor productivity (TFP) evaluation system, serving as a surrogate indicator of regional low-carbon economy. Inspired by their research, this paper proposes the concept of the LCEGE, a.k.a. the TFP of low-carbon economy, and uses it to evaluate the economic growth quality of the Belt in the modal shift to low-carbon economy. Our evaluation system has four input variables (i.e. the capital factor, the labor factor, the energy factor, and the carbon sink factor) and two output variables (i.e. the desired output GDP and the undesired output $CO_2$). The index selection and variable calculation are explained as follows:

(1) Capital factor (input variable): the capital factor refers to the capital stock of each region. According Shan (2008), the capital stock can be calculated by the perpetual inventory method: $K_{i,t}=I_{i,t}+(1-\delta)K_{i,t-1}$, where $I_{i,t}$ is the regional investment and $\delta$ is the capital depreciation rate. To eliminate the influence of inflation, the constant price of 1952 was taken as the base period value, and the nominal capital stock was deflated as the real capital stock.

(2) Labor factor (input variable): The labor factor is usually characterized by the regional employment. Drawing on relevant research, labor input is measured as the number of employees at the end of each year in each region.

(3) Energy factor (input variable): The energy factor stands for the three disposable energy sources, namely, coal, oil and natural gas. Considering the difference of the three energy sources in statistical units, the 10,000 tons of coal equivalent (TCE) was adopted as the unified unit of measurement. After conversion, the total consumption of the three energy sources was added up as the energy factor.

(4) Carbon sink factor (input variable): The carbon sink means the carbon sequestration effect of afforestation, which is the key to the modal shift to low-carbon economy. Here, the area of new forests formed by artificial greening projects is adopted to represent the carbon sink factor.

(5) GDP (desired output): Similar to the calculation of capital stock, the nominal GDP was deflated against the constant price of 1952, aiming to eliminate the negative effects of deflation.

(6) $CO_2$ (undesired output): The undesired output was defined as the perennial $CO_2$ emissions of each region. Whereas China has not released any specific statistics on $CO_2$ emissions, the output was estimated by the method specified in the *2006 IPCC Guidelines for National Greenhouse Gas Inventories*: the output value equals the product of the total energy consumption and the carbon emission coefficient. The latter was obtained from the Chinese national standard GB2589-81.

### *3.2. Selection of control variables*

In addition to input variables like capital, labor and carbon sink, the LCEGE is also affected and restricted by external macro factors like economic environment, technical innovation and government policy. Studies have shown that the modal shift to low-carbon economy is mainly motivated by industrial structure, energy structure, R&D investment, opening-up and environmental regulation (Xie and Song, 2017). Therefore, these five factors were selected as the control variables for the convergence in empirical analysis:

*(1) Industrial structure (IS):* This variable was expressed as the proportion of the added value of the regional secondary industry to the GDP. Compared with the primary and tertiary industries, the secondary industry consumes much energy, emits lots of carbon, and has excess capacity. The proportion has a negative impact on the LCEGE.

*(2) Energy structure (ES):* This variable was expressed as the proportion of coal consumption to the total energy consumption in a region. The intensive consumption of coal, a carbon-rich energy source, contributes greatly to the generation of $CO_2$. This proportion also has a negative impact on the LCEGE.

*(3) R&D investment (RD):* This variable was expressed as the proportion of regional R&D investment to the GDP. The regional R&D investment mirrors the technical innovation ability of the enterprises. The overall energy consumption of enterprises can be reduced by replacing some energy sources with innovative sources, thus promoting the LCEGE.

*(4) Opening-up (OP):* This variable was expressed as the proportion of the regional foreign direct investment to the GDP. The massive introduction of foreign capital brings in advanced management experience and low-carbon technologies, which promotes the production efficiency and low-carbon economy of the host country.

*(5) Environmental regulation (ER):* This variable was expressed as the proportion of investment

on industrial pollution control to the GDP in a region. The environmental regulation demonstrates the local government's intervention in environmental protection. If the government is concerned with the environment, it will invest more in environmental protection. This investment is conducive to the coordination between local economy and environment.

### *3.3. Data sources*

Considering the data availability and completeness, the empirical analysis was carried out using the panel data of the eleven provinces in the Belt. The input variables, output variables and control variables of each province were collected from the *China Statistical Yearbook*, *China Energy Statistical Yearbook*, *China Science and Technology Statistical Yearbook*, *China Environmental Yearbook*, *China Compendium of Statistics* and the local statistical yearbooks. Individual missing data were padded by linear interpolation.

## 4. LCEGE measurement and spatial correlation analysis

### *4.1. Static Temporal Variation in the LCEGE of the Belt*

Based on the input and output variables, the LCEGEs in 1998-2016 of the eleven provinces were measured on the MaxDEA and recorded in Table 1. It can be seen that the eleven provinces fell into four levels in terms of the LCEGE. Shanghai and Yunnan belong to the first level. Their LCEGEs were on the frontier in the observation period, i.e. the efficiency was always one. Zhejiang and Jiangsu belong to the second level. Their LCEGEs were respectively 0.8346 and 0.8214, which were close to the frontier, leaving the room for further improvement. Chongqing, Sichuan, Hubei and Hunan belong to the third level. Third LCEGEs were between 0.6 and 0.8, about the medium level of the entire Belt. Jiangxi, Anhui and Guizhou belong to the fourth layer. Their mean LCEGEs were below 0.6, lower than other regions in the Belt. To sum up, there are huge provincial differences in the LCEGE across the Belt; the provinces in the lower reaches are more efficient in low-carbon economic growth than those in the middle and upper reaches; there is a huge room for LCEGE improvement in the Belt.

### *4.2. Spatial correlation of the LCEGE in the Belt*

The Global Moran's I of the LCEGE between 1998 and 2016 in the Belt were calculated on the GeoDa, using Eqs.s (4)-(6) and the spatial adjacency matrix.

According to the results in Table 2, the Global Moran's I of the LCEGE was positive through the observation period and significant on the 5% or 1% level. This means the LCEGE of the Belt has positive spatial correlation, which confirms the spatial spillover effect of the low-carbon economy between the provinces in the Belt. Therefore, the possible spatial effect between the provinces should be fully considered in the convergence analysis of the LCEGE in the Belt. Otherwise, the empirical results may deviate greatly from the actual situation.

**Table 1.** Provincial LCEGEs in 1998-2016 of the Yangtze River Economic Belt

| ***Provinces*** | ***1998*** | ***2000*** | ***2002*** | ***2004*** | ***2006*** | ***2008*** |
|---|---|---|---|---|---|---|
| Shanghai | 1 | 1 | 1 | 1 | 1 | 1 |
| Yunnan | 1 | 1 | 1 | 1 | 1 | 1 |
| Zhejiang | 0.9033 | 0.8757 | 0.7886 | 0.8329 | 0.7916 | 1 |
| Jiangsu | 1 | 0.8278 | 0.8615 | 0.8516 | 0.7421 | 0.7546 |
| Chongqing | 0.6638 | 0.6388 | 0.6290 | 0.6429 | 0.7092 | 0.7537 |
| Sichuan | 0.6596 | 0.6245 | 0.6193 | 0.6252 | 0.7294 | 0.7034 |
| Hubei | 0.6417 | 0.6453 | 0.6442 | 0.6222 | 0.5713 | 0.6717 |
| Hunan | 0.6280 | 0.6881 | 0.6453 | 0.7253 | 0.6089 | 0.5709 |
| Jiangxi | 0.5707 | 0.5758 | 0.5884 | 0.5508 | 0.6439 | 0.5772 |
| Anhui | 0.5971 | 0.6015 | 0.6141 | 0.5615 | 0.5551 | 0.5998 |
| Guizhou | 0.4147 | 0.4612 | 0.5182 | 0.4603 | 0.4583 | 0.3542 |
| Province | 2010 | 2012 | 2014 | 2016 | Mean | |
| Shanghai | 1 | 1 | 1 | 1 | 1 | |
| Yunnan | 1 | 1 | 1 | 1 | 1 | |
| Zhejiang | 1 | 0.7965 | 0.8772 | 0.7755 | 0.8346 | |
| Jiangsu | 0.8584 | 0.7780 | 0.8762 | 0.7822 | 0.8214 | |
| Chongqing | 0.7019 | 0.8130 | 0.8612 | 0.7699 | 0.7231 | |
| Sichuan | 0.6899 | 0.7340 | 0.8502 | 0.6392 | 0.6844 | |
| Hubei | 0.6769 | 0.5820 | 0.6544 | 0.6589 | 0.6452 | |
| Hunan | 0.5589 | 0.6094 | 0.7020 | 0.7260 | 0.6370 | |
| Jiangxi | 0.6239 | 0.5781 | 0.5544 | 0.6297 | 0.5867 | |
| Anhui | 0.6076 | 0.5402 | 0.5680 | 0.6101 | 0.5843 | |
| Guizhou | 0.3633 | 0.3962 | 0.5656 | 0.5434 | 0.4576 | |

*Note: Only the data on even years were listed due to space limitation*

**Table 2.** Global Moran's I of the LCEGE in the Yangtze River Economic Belt

| *Year* | *Global Moran's I* | *E (I)* | *Mean* | *SD (I)* | *Z-score* |
|---|---|---|---|---|---|
| 1998 | 0.2234 | -0.0100 | -0.0365 | 0.1195 | 1.9531 |
| 1999 | 0.2145 | -0.0100 | -0.0371 | 0.1198 | 1.8740 |
| 2000 | 0.2317 | -0.0100 | -0.0398 | 0.1206 | 2.0041 |
| 2001 | 0.2254 | -0.0100 | -0.0405 | 0.1214 | 1.9390 |
| 2002 | 0.2373 | -0.0100 | -0.0414 | 0.1199 | 2.0626 |
| 2003 | 0.2458 | -0.0100 | -0.0424 | 0.1189 | 2.1514 |
| 2004 | 0.2434 | -0.0100 | -0.0456 | 0.1217 | 2.0822 |
| 2005 | 0.2507 | -0.0100 | -0.0387 | 0.1223 | 2.1316 |
| 2006 | 0.2498 | -0.0100 | -0.0353 | 0.1197 | 2.1704 |
| 2007 | 0.2358 | -0.0100 | -0.0373 | 0.1216 | 2.0214 |
| 2008 | 0.2534 | -0.0100 | -0.0368 | 0.1220 | 2.1590 |
| 2009 | 0.2601 | -0.0100 | -0.0397 | 0.1192 | 2.2659 |
| 2010 | 0.2574 | -0.0100 | -0.0358 | 0.1210 | 2.2099 |
| 2011 | 0.2492 | -0.0100 | -0.0409 | 0.1220 | 2.1246 |
| 2012 | 0.2362 | -0.0100 | -0.0416 | 0.1223 | 2.0131 |
| 2013 | 0.2320 | -0.0100 | -0.0409 | 0.1207 | 2.0050 |
| 2014 | 0.2457 | -0.0100 | -0.0393 | 0.1195 | 2.1398 |
| 2015 | 0.2482 | -0.0100 | -0.0423 | 0.1214 | 2.1269 |
| 2016 | 0.2501 | -0.0100 | -0.0416 | 0.1189 | 2.1876 |

## 5. Spatial regression analysis of LCEGE convergence

### *5.1. Measured results of common panel data model and spatial correlation test*

The LCEGE convergence of the Belt was verified by the least squares estimation in the ordinary panel data model. Meanwhile, the Matlab software was adopted to verify whether the residual term of the model has significant spatial autocorrelation. The results are recorded in Table 3 below. The estimation results of four different fixed effects models, namely, non-invariant model, space-invariant model, time-invariant model and dual-invariant model, are also presented in Table 3. The test data were compared to see which of the fixed effects models has the greatest explanatory power. On the estimation results of absolute beta-convergence models, the non-invariant model had a goodness-of-fit coefficient of only 0.0508; the dual-invariant model, which contains both time and space invariances, had a goodness-of-fit coefficient of 0.2857, greater than any other models. This means the dual-invariant model boasts the best overall fitness. The same was observed in the estimation results of conditional beta-convergence models: the dual-invariant model had a goodness-of-fit coefficient of 0.4904, greater than any other models. To sum up, the dual-invariant model enjoys the optimal fitness in both absolute and conditional beta-convergences. In addition, the dual-invariant model outperformed the other three models in the *Log-L* value (246.6075) under absolute beta-convergence, so did the model under conditional beta-convergence. The above results show that the dual-invariant model has greater explanatory power than the non-invariant, space-invariant and time-invariant models. As a result, the estimation results of this model were adopted to explain the LCEGE convergence in the Belt. The lower half of Table 3 presents the spatial autocorrelation test results on the residual term in the common model. In the dual-invariant model of absolute beta-convergence, the *LM-lag* stood at 6.6822, passing the test on the significance level of 1%; the *LM-err* was 5.1717, also significant on the 1% level. Similarly, the dual-invariant model of conditional beta-convergence passed the tests on the 1% and 5% significance levels, with the *LM-lag* and the *LM-err* being 5.7652 and 4.4859, respectively. It is safe to say that the residual term of the ordinary panel data model has significant spatial autocorrelation, which cannot be solved by the traditional least squares estimation. Thus, it is necessary to use the spatial econometrics for retest. Besides, the *LM-lag* statistic was greater than the *LM-err* statistic in both models, indicating that the SAR is better than the SEM. This means the SAR is more suitable for our empirical test.

### *5.2. Estimation results of spatial panel data models*

Since the least squares estimation of the ordinary panel data model cannot solve the spatial autocorrelation problem of the residual term, the convergence was simulated again by the maximum likelihood method of the spatial econometric model. The estimation results of the two spatial panel data models, SAR and SEM, were thus obtained (Table 4). It can be seen that both the spatial lag term *W*dep.var* of the SAR model and the spatial error term *spat.aut* of the SEM model passed the test on the 1% significance level, which further verifies the applicability of spatial econometric model. Compared with the common panel data model, the spatial econometric model achieved a high goodness-of-fit coefficient and a high log likelihood *Log-L*, indicating that the spatial econometric model is better than the common panel data model. In addition, the SAR surpassed the SEM in *Log-Lunder* both absolute and conditional beta-convergences.

**Table 3.** Estimation and verification results of common panel data model

| Variable | Absolute beta-convergence | | | |
|---|---|---|---|---|
| | Non-invariant | Space-invariant | Time-invariant | Dual-invariant |
| $\ln y_0$ | -0.0791*** (-3.2401) | -0.5600*** (-8.6976) | -0.0750*** (-3.2031) | -0.5725*** (-8.8773) |
| *IS* | | | | |
| *ES* | | | | |
| *RD* | | | | |
| *OP* | | | | |
| *ER* | | | | |
| $R-squared$ | 0.0508 | 0.2775 | 0.0495 | 0.2857 |
| $Log-L$ | 208.4458 | 236.2135 | 217.4881 | 246.6075 |
| $DW$ | 1.8772 | 1.3076 | 2.0781 | 2.0674 |
| $LM-lag$ | 8.2344*** | 31.1235*** | 0.8037 | 6.6822*** |
| $Robust\ LM-lag$ | 2.8684* | 6.5349*** | 0.0433 | 2.2563* |
| $LM-err$ | 7.0661*** | 25.0644*** | 0.8850 | 5.1717*** |
| $Robust\ LM-err$ | 2.5235* | 4.8758** | 0.1246 | 1.7458 |
| **Variable** | **Conditional beta-convergence** | | | |
| | No-invariant | Space-invariant | Time-invariant | Dual-invariant |
| $\ln y_0$ | -0.1477*** (-4.2616) | -0.6080*** (-9.1882) | -0.1472*** (-4.3105) | -0.7143*** (-10.1513) |
| *IS* | -0.0006 (-0.3156) | -0.1381*** (2.6105) | -0.0010 (-0.4700) | -0.1010** (1.9538) |
| *ES* | -0.1328*** (-2.5655) | -0.1831** (-2.1763) | -0.1332*** (-2.6445) | -0.1287* (-1.8091) |
| *RD* | 0.4562*** (2.3819) | 0.2585** (1.9275) | 0.3108** (2.2165) | 0.3754*** (2.7544) |
| *OP* | 0.4922* (1.8228) | 0.5691** (2.1794) | 0.5469** (2.0138) | 0.4205* (1.7256) |
| *ER* | 0.0780 (0.8994) | 0.1556 (1.0034) | 0.1606* (1.5419) | 0.0413 (0.1421) |
| $R-squared$ | 0.0939 | 0.3091 | 0.0950 | 0.4904 |
| $Log-L$ | 213.0425 | 240.6419 | 222.3436 | 299.8959 |
| $DW$ | 1.8901 | 1.9334 | 2.1113 | 2.1315 |
| $LM-lag$ | 11.0020*** | 19.9854*** | 0.9679 | 5.7652*** |
| $Robust\ LM-lag$ | 3.0207* | 4.4515** | 5.6609*** | 2.0579* |
| $LM-err$ | 7.6940*** | 17.5406*** | 1.5620 | 4.4859** |
| $Robust\ LM-err$ | 2.7137* | 4.2067** | 6.2550*** | 1.8999 |

*Note: The data in () is the T-test value; *, ** and *** refers to the significance levels of 10%, 5% and 1%, respectively; Model estimation and spatial autocorrelation test were conducted on Matlab 7.11*

This means the SAR model has more explanatory power than the SEM model. Thus, this paper decides to analyze the estimation result on each explanatory variable in the SAR. On the estimation results of the SAR under absolute beta-convergence, the estimated coefficient of $lny_0$ was negative and passed the test on the 1% significance level, revealing that the LCEGE in the Belt has absolute beta-convergence. According to the principle of the neoclassical economic growth model $\beta(|\beta|=1-e^{-\theta T}, where\ \theta(\theta=-\frac{1}{T}\ln(1-\beta)))$ is the convergence rate and $T$ is the length of sample data observation period.), the absolute convergence rate of the LCEGE in the Belt was 5.85%, faster than the 4.47% obtained by the common panel data model. This confirms the significant spatial spillover effect of the LCEGE between the provinces in the Belt: the LCEGE of a province will increase with the low-carbon economic growth in other provinces.

Thus, the LCEGE convergence will pick up speed after introducing the spatial effect. Considering the huge provincial difference in the LCEGE in the Belt, it is necessary to discuss the conditional convergence of the LCEGE in the Belt, such as to identify the reasons for the provincial difference and convergence.

On the estimation results of the SAR under conditional beta-convergence, the estimated coefficient of $lny_0$ was negative on the 1% significance level, indicating that the LCEGE of the Belt has conditional beta-convergence. The convergence rate of the LCEGE was 7.54%. Meanwhile, the goodness-of-fit of the conditional beta-convergence model was better than the absolute beta-convergence model, after the addition of the control variables.

**Table 4.** Estimation and verification results of spatial econometric model (dual invariant model)

| *Variable* | *Absolute beta-convergence* | | *Conditional beta-convergence* | |
|---|---|---|---|---|
| | *SAR* | *SEM* | *SAR* | *SEM* |
| $\ln y_0$ | -0.6708*** (-9.8946) | -0.6595*** (-9.2722) | -0.7612*** (-11.2725) | -7.5617*** (-10.9578) |
| *IS* | | | -0.1310*** (-2.5183) | -0.1258*** (-2.3554) |
| *ES* | | | -0.1484** (-2.1531) | -0.1562** (-2.2273) |
| *RD* | | | 0.3882*** (2.9306) | 0.3864** (2.8423) |
| *OP* | | | 0.4261** (1.9748) | 0.4098** (1.9069) |
| *ER* | | | 0.0634 (0.2210) | 0.0414 (0.1445) |
| $W * dep.\mathrm{var}.$ | -0.0699*** (-3.8219) | | -0.0597*** (-3.4147) | |
| $spat.aut.$ | | -0.0569*** (-3.3984) | | -0.0464** (-2.8335) |
| $R-squared$ | 0.4475 | 0.4344 | 0.6085 | 0.5957 |
| $Log-L$ | 286.9298 | 280.6936 | 350.2200 | 339.1485 |

*Note: The data in () is the T-test value; *, ** and *** refers to the significance levels of 10%, 5% and 1%, respectively*

It can be seen that the control variables like the industrial structure, energy structure, R&D investment, opening-up and environmental regulation have important impacts on the LCEGE convergence in the Belt. The influence of each control variable in the conditional convergence model is summed up as follows: (1) The industrial strucutre (IS) had a negative impact on the LCEGE convergence on the 1% significance level, which verifies the previous hypothesis. This means the modal shift to low-carbon economy is hindered by the growing proportion of the added value of the regional secondary industry to the GDP. (2) The energy structure (ES) had a negative impact on the LCEGE convergence on the 5% significance level, indicating that the energy structure of the Belt is and will be dominated by coal in the short term. Thus, the key to realize the modal shift is to increase the consumption of clean energy. (3) The estimated coefficient of the R&D investment (RD) is positive and passed the test on the 1% significance level, revealing that a growing regional R&D can indeed promote the LCEGE convergence.

Hence, technical progress is an important means to save energy and reduce emissions. (4) Opening-up (OP) had a singificant positive effect on the LCEGE convergence on the 5% significance level, which also verifies the previous hypothesis. (5) Environmental regulation (ER) had a positive impact on the LCEGE convergence, but the influence did not pass the significance test. A possible reason is that the envrinmental regulation is too weak to force enterprises to cut emissions.

The verification results under conditional beta-convergence also show that the spatial difference of the LCEGE in the Belt mainly lies in the difference of external factors, such as industrial structure, energy structure, R&D investment, opening-up and environmental regulation. Backward regions must improve these external factors to catch up with developed regions in the LCEGE, leading to the overall LCEGE improvement in the Belt.

## 6. Conclusions

This paper introduces the carbon sink factor to evaluation system for the LCEGE, and then evaluates the LCEGE in 1998~2006 of the eleven provinces in the Yangtze River Economic Belt by the mSBM method. Then, the spatial difference and convergence of the LCEGE in the Belt were investigated by spatial econometric method. The main results are as follows: The LCEGEs of all provinces, except for Shanghai and Yunnan, need to be further improved towards the efficient frontier; the provinces in the lower reaches have greater LCEGEs than most provinces in the middle and upper reaches, revealing the regional imbalance of low-carbon economy in the Belt; the Global Moran's I test shows a significant spatial correlation of the LCEGE in the Belt, with an obvious regional spatial clustering effect; the empirical results of the spatial correlation model demonstrate that the LCEGE in the Belt has a spatial spillover effect, and the LCEGE gap between different provinces is narrowing steadily at an absolute convergence rate of 5.85%; the LCEGE has a significant positive correlation with the R&D investment and opening-up, a significant negative correlation with industrial structure and energy structure, and an insignificant correlation with environmental regulation.

Based on the above conclusions, the Belt should prioritize the following tasks to speed up the modal shift to low-carbon economy. First, the Belt should continue to pursue coordinated development between regions, solving the regional imbalance in low-carbon economy. Second, the Belt should further boost the proportion of the tertiary industry (service industry) in the GDP, and reduce that of the secondary industry. Third, the Belt should attach greater importance to scientific research, and implement the strategy of technical progress by investing more in R&D. Fourth, the Belt should vigorously promote the clean energy strategy, build a clean energy base, and gradually reduce the presence of fossil energies in the energy structure. Fifth, the Belt should increase the degree of opening-up, optimize the access system for foreign investments, and bring in more high-tech, low-carbon foreign enterprises. Sixth, the Belt should strengthen the environmental regulation, and charge a higher fee on industrial pollution, forcing enterprises to save energy and reduce emissions.

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