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Convergence of carbon intensity in the Yangtze River Delta, China

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Abstract

As China’s industrialization and urbanization have grown rapidly in recent years, China’s CO₂ emissions rose from 3405.1799 Mt to 10,249.4630 Mt from 2000 to 2013, and it has reached the highest levels in the world since 2006. Chinese government has emphasized the importance of reducing carbon emissions and set the target of reducing carbon intensity to 60–65% of 2005 levels by 2030. Investigating the convergence of carbon intensity can identify the convergence rate, which is helpful in guiding allocations of carbon intensity reduction. The Yangtze River Delta is one of the key carbon emission regions in China, with higher urbanization levels and larger carbon emissions; thus, we employed prefecture-level panel data derived from grid data between 2000 and 2010 to examine whether the convergence of carbon intensity exists across prefecture-level cities in the Yangtze River Delta. Spatial panel data models were utilized to investigate β-convergence of carbon intensity. The results indicated that carbon intensity showed divergence during 2002–2004 and α-convergence over other periods (2000–2002 and 2004–2010). Carbon intensity exhibited stochastic convergence, indicating that the shocks to carbon intensity relative to the average level of carbon intensity are only transitory. There was a spatial spillover effect and β-convergence of carbon intensity, suggesting that prefecture-level cities with higher carbon intensity would decrease rapidly in the Yangtze River Delta. Our results highlight the importance of considering the present state of carbon intensity, spatial factors, and socioeconomic factors such as industrial structure and economic levels during allocation planning for reducing carbon intensity.

1. Introduction

Carbon dioxide is one of the key greenhouse gases causing global warming; most world governments have recognized the risk of global warming and urgency for carbon reduction. With rapid industrialization and urbanization, China’s CO₂ emissions were 3405.1799 Mt in 2000, and it increased rapidly with the average growth rate of 8.2% from 2000 to 2013. China’s CO₂ emissions are at their highest since 2006 (Gregg, Andres, & Marland, 2008). During the same period of 2000–2013, China’s contribution to global carbon emissions rose from 13.7% to 28.6% (Fig. 1) (World Bank, 2016). To mitigate carbon emissions and global warming, China has made different environmental policies and taken effective measures (Li & Lin, 2016; Wu, Wu, Guo, & Cheong, 2016). In particular, China has raised a target of decreasing carbon intensity (CO₂ emissions divided by gross domestic product (GDP)) to 40–45% of 2005 levels by 2020 (Li et al., 2016; Qiu, 2009). In the Twelfth Five-Year (2011–2015) Plan drafted by China’s State Council, the target of carbon emission were allocated to the provinces for the first time (Hao, Liao, & Wei, 2015a). China pledged that the peak of CO₂ emissions would achieve around 2030, carbon intensity would decline to 60%–65% of 2005 levels by 2030 in China (National Development and Reform Commission of China, 2015). The allocation of carbon emission reductions has attracted the attention of scholars (Liao, Zhu, & Shi, 2015; Yu, Wei, & Wang, 2014; Zhang, Wang, & Da, 2014), but there are relatively few studies from the perspective of convergence for carbon intensity (Hao et al., 2015a; Wang, Zhang, Huang, & Cai, 2014b). Many climate policies assume that there is convergence (McKibbin & Stegman, 2005; McKibbin, Pearce, & Stegman, 2007; Pettersson, Madsen, Acar, & Söderholm, 2014). The convergence of carbon intensity can
provide an important reference for the equal allocation of carbon intensity targets and contribute to the projections of carbon intensity (McKibbin & Stegman, 2005; Pettersson et al., 2014). Meanwhile, the existing convergence of carbon intensity is helpful to make better environmental policies and it is a necessary condition to achieve the peak of carbon emission (Jobert, Karanfil, & Tykhonenko, 2010; McKibbin & Stegman, 2005). Analyzing the convergence of carbon intensity is helpful to cognize the change mechanism of carbon intensity and to set evidence-based policies for carbon intensity targets. Convergence of carbon intensity is of particular concern to policymakers in China, and government establishes some important targets of decreasing carbon intensity (Li & Lin, 2016; Wu et al., 2016). Instead of equal allocation of carbon intensity to each province, the allocation of carbon intensity to prefecture-level city can be more effective (Wu et al., 2016). Therefore, investigation of the convergence of carbon intensity is important for policymakers to provide suggestions in allocating carbon intensity targets according to carbon intensity rules.

Solow (1956) first proposed the theory of convergence in 1956, which has become important in modern economic growth research (Hao, Zhang, Zhong, & Li, 2015b). To our knowledge, Strazichich and List (2003) probably made the first attempt to test the conditional and stochastic convergence in 21 industrial countries during the period of 1960–1997 and found that there was significant convergence. Pettersson et al. (2014) reviewed the development literature of the convergence. The research on the scale of carbon convergence mainly focuses on countries (Fallahi & Voia, 2015; Jobert et al., 2010; McKitrick & Wood, 2013; Ordás Criado & Grether, 2011) or provinces (Hao et al., 2015a; Wang & Zhang, 2014; Yang, Zhang, Sheng, & Shackman, 2016). For example, Ordás Criado and Grether (2011) investigated the convergence of per capita CO2 in 166 world areas during 1960–2000 and found that there were different convergence states during different periods. Wang and Zhang (2014) investigated the convergence of CO2 in China’s six sectors in provincial level during 1996–2010 and found that there was convergence in these sectors.

Different methods have been developed to investigate the convergence of carbon emissions in recent years. The system generalized method of moments (GMM) was utilized by Yang et al. (2016) to investigate the convergence of CO2 emissions during 1998–2012 and found no convergence. Bayesian shrinkage estimation (BSE) was applied by Jobert et al. (2010) to examined the convergence of CO2 emissions during 1971–2006 and they found that there was absolute convergence. Semi-parametric and non-parametric models were employed to investigate the convergence of nitrogen oxides and sulfur oxides in 25 European countries during 1980–2005 (Ordás Criado, Valente, & Stengos, 2011). The log r test was used by Wang et al. (2014b) to verify the convergence of carbon intensity in China during 1995–2011 and they found that there was divergence at the national level but convergence at the provincial level. Spatial lag model (SLM) was utilized by Huang and Meng (2013) to investigate CO2 emissions convergence and they found that the convergence rate showed an increasing trend when considering spatial effects. Spatial autoregressive (SAR) model and spatial error model (SEM) was used by Yu (2012) to verify the convergence of Chinese energy intensity and the result showed absolute β-convergence across provinces.

Although the existing studies have focused on the convergence of carbon emissions (Evans & Kim, 2015; Pettersson et al., 2014; Wang & Zhang, 2014; Wu et al., 2016), there were three major limitations. First, the research scale mainly focuses on countries (Fallahi & Voia, 2015; McKitrick & Wood, 2013; Ordás Criado & Grether, 2011) or provinces (Hao et al., 2015a; Wang & Zhang, 2014; Wang et al., 2014b). Second, previous researches on carbon emissions convergence have focused on carbon emissions per capita (Jobert et al., 2010; Pettersson et al., 2014); however, few have investigated the convergence of carbon intensity (Hao et al., 2015a; Wang et al., 2014b; Zhu et al., 2014). Third, most studies have ignored the effects of spatial factors on carbon emission convergence, which may increase the biases of results.

To address these knowledge gaps, the current paper utilizes spatial econometric models to examine the convergence of carbon intensity in the Yangtze River Delta (YRD) during the period of 2000–2010, using the prefecture-level city as the basic research unit and considering spatial spillover effects and spatial dependence. To our knowledge, this is the first attempt to investigate the convergence of carbon intensity across prefecture-level cities using grid data in the YRD. Compared with provincial data, prefecture-level city data can provide more accurate and detailed results; meanwhile, prefecture-level cities are the main source of carbon emissions. In addition, we investigate the convergence of carbon intensity rather than carbon emissions per capita, which can better assist policymakers in allocating the reduction targets of carbon emissions. Furthermore, we consider spatial spillover effects and spatial dependence, utilizing spatial econometric models that examine β-convergence, better simulating the actual values.

The paper investigates these questions: (1) Is there convergence of carbon intensity during the period of 2000–2010 in the YRD? (2)
What are the major factors effecting convergence of carbon intensity? (3) What policy is suitable to decrease the annual growth of carbon intensity?

2. Data source and methodology

2.1. Research area and data source

The YRD includes Shanghai City, Jiangsu Province and Zhejiang Province, includes 25 prefecture-level cities (Fig. 2) and is one of the key carbon emission regions in China (Wang et al., 2014a). The YRD has developed into one of the regional economic engines in China, with a high urbanization level, large carbon emissions and low carbon intensity. The YRD urban agglomeration is the largest one in China, and also one of six largest urban agglomerations in the world (World Heritage Encyclopedia, 2015). In 2013, GDP per capita of the 12,149 dollars (USD) was 1.7 times of the Chinese average, and the urbanization rate of 67.9% was 1.3 times as high as the national average. It accounted for 2.2% of China’s land area, 11.6% of China’s population, while it generated 20.2% of China’s GDP and produced 13% of China’s energy CO2 emissions, with a lower carbon intensity of 0.7 times lower than the national average in 2013 (National Bureau Statistics of China, 2014; 2014a).

We utilized a balanced panel of prefecture-level cities in the YRD during the period of 2000–2010. CO2 data were obtained from the Emission Database for Global Atmospheric Research (EDGAR), the greenhouse gas emissions database with the highest spatial accuracy on a global level (European Commission Joint Research Centre (JRC) & Netherlands Environmental Assessment Agency (PBL), 2013). EDGAR has been widely used in the investigation of urban pollutant and CO2 emissions (McDonald, McBride, Martin, & Harley, 2014; Schneising et al., 2013). We used CO2 emissions data of 0.1° × 0.1° grid cells; the distance of every grid is approximately 10 km, which meets accuracy requirements of many studies including the current one (Marcotullio, Sarzynski, Albrecht, & Schulz, 2012; Wang et al., 2014a). The CO2 emissions were calculated based on production, mainly including energy industry, transformation non-energy use, combustion in manufacturing industry, international and domestic aviation, road transportation, non-road ground transport, international and domestic shipping, energy for buildings, fugitive from solid, oil production and refineries, non-metallic mineral processes, chemical processes solvents, metal processes, agricultural soils, large scale biomass burning, solid waste disposal and fossil fuel fires (European Commission Joint Research Centre (JRC) & Netherlands Environmental Assessment Agency (PBL), 2013). We utilized EDGAR and vector data of prefecture-level cities to precisely calculate CO2 emissions in ArcGIS 10.2 (ESRI Inc., Redlands, California, USA). GDP (converted in constant prices in 2000), population, secondary industry values and the area of each prefecture-level city were obtained from the China Statistical Yearbook for Regional Economy (2001–2011) (National Bureau Statistics of China, 2001–2011).

2.2. Methodology

Convergence mainly includes three types: σ-convergence, stochastic convergence and β-convergence (Fallahi & Voia, 2015; Wang & Zhang, 2014).

2.2.1. σ-convergence

σ-convergence has many measures, such as standard deviation, deviation, and coefficient of variation (Adhikari & Chen, 2014). The σ-convergence of carbon intensity is measured by standard deviation, using the following equation (Adhikari & Chen, 2014):

\[ \sigma_{it} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (CI_{it} - \overline{CI}_t)^2} \]  

where \( i \) and \( t \) are the prefecture-level city and year, respectively; \( \sigma_{it} \) denotes the standard deviation of carbon intensity; \( n \) is the
number of prefecture-level cities in the YRD; \( CI_k \) is the carbon intensity; and \( \overline{CI} \) denotes the mean value of carbon intensity.

### 2.2.2. \( \beta \)-Convergence

\( \beta \)-convergence indicates that prefecture-level cities with higher initial levels of carbon intensity tend to decrease faster (Hao et al., 2015a). \( \beta \)-convergence includes absolute \( \beta \)-convergence and conditional \( \beta \)-convergence. The equation of absolute \( \beta \)-convergence model is as follows (Adhikari & Chen, 2014):

\[
\ln(\frac{CI_{it+1}}{CI_{it}}) = a + b \ln CI_{it} + \varepsilon_{it} \tag{2}
\]

where \( \ln(\frac{CI_{it+1}}{CI_{it}}) \) is the annual growth rate of carbon intensity; \( a \) denotes the constant; \( b \) denotes the coefficient of \( \ln CI_{it} \); and \( \varepsilon_{it} \) denotes the error term. Other variables show the same meaning as in equation (1). When the value of \( b \) is significantly negative, this indicates that there is \( \beta \)-convergence of carbon intensity across prefecture-level cities in the YRD (Wang & Zhang, 2014).

Referring literatures, we chose GDP per capita (the ratio of GDP to population in each prefecture-level city) (PGDP) (Zhu et al., 2014), industrial structure (GDP from second industry divided by total GDP in each prefecture-level city) (IS) (Guo et al., 2014) and population density (the population divided by the area of each prefecture-level city) (PD) (Strazicich & List, 2003) as control variables to investigate the conditional \( \beta \)-convergence of carbon intensity. Table 1 shows descriptive statistics of all related variables. GDP per capita is taken as a representation of economic development level, as it has an important impact on carbon intensity (Zhao, Burnett, & Fletcher, 2014). Wang, Zhang, and Liu (2016b) found the more developed prefecture-level city the more likely to reduce carbon intensity in China. The secondary industry is the main source of CO2 emissions, and thus the higher the proportion of the secondary industry’s value in GDP, the more difficult to reduce carbon intensity (Hao et al., 2015a). The population factor is usually utilized to analyze carbon emissions, but there is a variable relationship between population density and carbon intensity. Zhao et al. (2014) suggested that increasing population density would reduce carbon intensity. Hao et al. (2015b) proposed that higher population density may increase the degree of industrialization, which causes higher carbon intensity. The equation of conditional \( \beta \)-convergence model is as follows (Adhikari & Chen, 2014):

\[
\ln(\frac{CI_{it+1}}{CI_{it}}) = a + b \ln CI_{it} + \beta_c X_{it} + \varepsilon_{it} \tag{3}
\]

where \( X_{it} \) is the control variable; \( \beta_c \) represents the coefficients of control variables; and other variables share the same meanings as in equations (1) and (2).

To consider the interaction effect between carbon intensity and other control variables, the equation of conditional \( \beta \)-convergence model is as follows (Brännlund, Lundgren, & Söderholm, 2015):

\[
\ln(\frac{CI_{it+1}}{CI_{it}}) = a + b \ln CI_{it} + \beta_c X_{it} + \beta_d CI_{it} X_{it} + \varepsilon_{it} \tag{4}
\]

Table 1

| Variable                  | Unit                  | Minimum  | Maximum  | Mean     | Standard deviation | Observations |
|---------------------------|-----------------------|----------|----------|----------|--------------------|--------------|
| \( \ln(GDP_{t+1}/GDP_t) \) | %                     | -0.1090  | 0.0759   | -0.0374  | 0.0382             | 250          |
| Carbon intensity          | ton/10,000 CNY        | 0.1654   | 7.6714   | 2.8946   | 1.5595             | 250          |
| GDP per capita            | constant price of 2000 CNY | 3971.739 | 85063.1321 | 25885.3598 | 17190.3268 | 250 |
| Industrial structure     | %                     | 33.2544  | 65.2090  | 53.5165  | 6.5227             | 250          |
| Population density       | Persons/area          | 143.7045 | 2208.9576 | 694.0316 | 358.2495 | 250 |

Notes: \( \ln(GDP_{t+1}/GDP_t) \) represents the annual growth rate of carbon intensity at year \( t+1 \).
\[
\ln(C_{it+1}/C_{it}) = \alpha + \beta \ln C_{it} + \beta_d x_{it} + \beta_q C_{it}x_{it} + \mu_i + \eta_t + u_{it}
\]

where \(\lambda\) represents the spatial error coefficient; \(u_{it}\) is the random error term; and other variables share the same meaning as in equations (5) and (6).

2.2.3. Stochastic convergence

A unit root test is usually utilized to verify stochastic convergence (Strazicich & List, 2003). The Augmented Dickey–Fuller (ADF) test is an uncommon unit root test, while the Levin–Lin–Chu (LLC) test is a common unit root test (Hao et al., 2015a); thus, both ADF and LLC are utilized in the study. We applied the LLC test and ADF test using Eviews 8.0 (IHS Global Inc., Irvine, California, USA).

3. Results

3.1. Spatial characteristics of carbon intensity

Carbon intensity varies widely in the YRD. As shown in Fig. 3, carbon intensity is divided into four types using the natural breaks (Jenks) classification method. The higher values are mainly concentrated in Yangzhou and Zhenjiang, which indicates the existence of a local cluster of higher carbon intensity. The lower values are mainly concentrated in jinhua and Zoushan, which show a scatter distribution. The highest value of 5.6157 \$/10,000 CNY in Zhenjiang is more than 35 times greater than the lowest value of 0.1575 \$/10,000 CNY in Zoushan.

Getis-Ord general G is used to measure the degree of clustering for either low values or high values in ArcGIS 10.2. The observed Getis-Ord general G is 0.0467, and the expected Getis-Ord general G is 0.0400, with a p value of 0.0143. The observed Getis-Ord general G is larger than the expected Getis-Ord general G, with a significant spatial cluster of high values in the YRD (Fischer & Getis, 2009). To investigate the local spatial agglomeration characteristics, the local spatial association index Getis-Ord Gi* was calculated using ArcGIS 10.2 to identify statistically significant cold spots (prefecture-level cities with lower values of carbon intensity) and hot spots (prefecture-level cities with higher values of carbon intensity) (Fischer & Getis, 2009). As shown in Fig. 4, cold spots are mainly concentrated in Hangzhou and Zoushan, with a relatively fragmented distribution. Hot spots are mainly concentrated in Huai’an, Yangzhou, Zhenjiang and Nanjing, forming a plurality of high carbon intensity cores, suggesting the existence of spatially local clusters of high carbon intensity and therefore key areas for reducing carbon intensity.

3.2. σ-convergence

The overview of the change trends of carbon intensity and \(\sigma\) is shown in Fig. 5. Carbon intensity has a maximum value of 3.1528 tons CO\(_2\)/10,000 CNY in 2000 and a minimum value of 2.3955 tons CO\(_2\)/10,000 CNY in 2010; it decreased by 24.02% from 2000 to 2010. Carbon intensity shows an overall downward trend in three main stages: the first one is from 2000 to 2002, a decreasing trend; the second one is from 2002 to 2004, a rising trend; and the third stage, an again decreasing trend. Carbon intensity shows increasing trends in 2003, 2004 and 2008. The standard deviation of carbon intensity was calculated to investigate the σ-convergence. Similar to carbon intensity, the maximum value of \(\sigma\) is 1.7577 and the minimum value is 1.2893 in 2010. Overall, it descended by 26.65% from 2000 to 2010. During the period of 2002–2004, \(\sigma\) increased, indicating the divergence of carbon intensity during 2002–2004, and the absolute disparities of carbon intensity increased. \(\sigma\) has declined over other periods (2000–2002 and 2004–2010), indicating the σ-convergence of carbon intensity and the absolute disparities of carbon intensity decreased.

3.3. Stochastic convergence

The values of the LLC test and the ADF test are −10.365 and 243.162, respectively, and \(p\) values are <0.0001 and <0.0001, respectively, rejecting the null hypothesis of a unit root. There is no unit root, and carbon intensity exhibits a stationary series; thus, there is stochastic convergence.

3.4. β-Convergence

Moran’s I value of the annual growth rate of carbon intensity is 0.7681 during 2000–2010, with a \(p\) value of <0.0001, suggesting a significant positive spatial autocorrelation. This annual growth rate of carbon intensity shows a spatial agglomeration across prefecture-level cities in the YRD: prefecture-level cities with higher annual growth rates of carbon intensity cluster together, while the prefecture-level cities with lower annual growth rates of carbon intensity also cluster together. Therefore, spatial factors should be considered when the β-convergence of carbon intensity is investigated. Both SLM and SEM were employed to judge whether there is β-convergence of carbon intensity.

The spatial Hausman value is 23.7227, and the \(p\) value is < 0.0001, indicating that spatial fixed effects should be considered (Pace & LeSage, 2008). We utilized Lagrange Multiplier (LM) tests to select a suitable model. Lagrange Multiplier lag (LM-lag) and Lagrange Multiplier error (LM-error) are 298.1018 and 307.8771, respectively, and \(p\) values are <0.0001 and < 0.0001, respectively. Robust LM-lag and robust LM-error are 0.1938 and 9.9692, respectively, and \(p\) values are 0.6600 and 0.0020, respectively. Therefore, the SEM is more suitable, while the spatial Durbin model (SDM) should be considered (LeSage & Pace, 2009). The SDM can be simplified to the SLM or the SEM (Burridge, 1981). The Wald test is 0.0502, and the \(p\) value is 0.8227, indicating that the SEM is more suitable (Burridge, 1981). Thus, we employ the SEM with spatial fixed effects to investigate the absolute β-convergence. According to the same methods, we choose the SLM with spatial fixed effects to investigate the conditional β-convergence.

In the second column of Table 2, the goodness of fit (R\(^2\)) of the SEM (0.1307) is larger than that of the panel data models (0.0444), indicating that SEM can better simulate the actual values. The coefficient of \(\ln(CI)\) is significantly negative, indicating that there is absolute β-convergence of carbon intensity. The convergence speed of the SEM is 0.0912 larger than that of non-spatial models (0.0789). The spatial error coefficient (\(\lambda\)) is positive and significant at the 1% level, suggesting that there is spatial agglomeration of the annual growth rate of carbon intensity and it may be influenced by other factors. Therefore, it is necessary to investigate the conditional β-convergence based on spatial econometric models.

The estimated result of conditional convergence is shown in columns 3 and 4 of Table 2, the interaction effect is included in Model 3. The rates of convergence in all prefecture-level cities are assumed same in Model 2, but the rates are assumed different between the prefecture-level cities in Model 3. The coefficient of carbon intensity is significantly negative, indicating that conditional β-convergence exists: prefecture-level cities converge to different steady states and have different speed of convergence. The spatial autoregressive coefficient is significantly positive, suggesting that the decrease in annual growth rate of carbon intensity in
neighboring prefecture-level cities can cause decreases in the prefecture-level city. In Model 3, significant control variable is only industrial structure, with p values of 0.0737. Insignificant control variables are population density and GDP per capita with p values of 0.7906 and 0.4143, respectively. The interaction effects of industrial structure and GDP per capita are significant, with p values of 0.0064 and < 0.0001. Thus, both industrial structure and GDP per capita have important influences on the conditional β-convergence of carbon intensity. The conditional β-convergence speed of 0.3805 is obviously larger than the absolute β-convergence speed of 0.0912, indicating that the control variables accelerate the convergence rate. The conditional β-convergence speed including interaction effect is larger, indicating that interaction effect also accelerates the convergence rate.

4. Discussion

Carbon intensity changed widely in the YRD due to variable geographic positions, resource endowments and economic levels. Chinese government executed stricter energy policies in the Tenth Five-Year Plan Period (2000–2005) by adjusting the energy and industrial structures (Yuan & Zuo, 2011). Land use change, particular farmland converted to settlement and industry parks, also change the carbon emission in the YRD (Lai et al., 2016; Zhang et al., 2015). With the effective measures, carbon intensity presented a downward trend during 2000–2002 and 2004–2010 (Fig. 5). Carbon intensity showed an increasing trend in 2003, 2004 and 2008. Domestic and international events may affect the trends. In 2003, Severe Acute Respiratory Syndrome (SARS) broke out in China,
causing a serious impact on human health and economic activities, the effects of which continued into the following year (Zhong et al., 2003). In 2008, a global financial crisis engulfed the world (Lu, Yang, Huang, Chuai, & Wu, 2015; Wu et al., 2015) with serious impacts on social and economic development in the YRD. The YRD has a processing trade development model in the low added value segment of high-end products (labor-intensive areas, low value-added sectors), both low efficiency and high risk (Chen, 2007). It is easily affected by global economic fluctuations, as a decrease in external demand leads to a substantial decrease in exports. Internal and external factors change economic development, which cause the change of carbon intensity. China executed a series of measures to address the global financial crisis; the “four trillion plan” was implemented by the Chinese government in 2008 (Chen, Pan, Wang, & Shen, 2016), and industrial transformation and upgrading was executed in the YRD, which pulled economic development out of the trough (Liu & Li, 2015).

The stochastic convergence of carbon intensity indicates that shocks to carbon intensity relative to the average level of carbon intensity are only transitory (Pettersson et al., 2014). Random shocks could disappear over time (Jobert et al., 2010); the carbon intensity of each prefecture-level city may be close to the average carbon intensity of the whole YRD.

The β-convergence of carbon intensity means that prefecture-level cities with higher initial carbon intensity will experience more rapid reductions and eventually catch up to prefecture-level

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**Fig. 4.** Cold spots and hot spots of carbon intensity in 2010 in the Yangtze River Delta, China.
cities with lower carbon intensity (Pettersson et al., 2014). It also indicates that as time goes on, differences in carbon intensity are decreasing across the prefecture-level cities in the YRD. This is perhaps the result of differences in factors affecting carbon intensity, such as decreases in technical levels, economic levels and industrial structure. Therefore, the prefecture-level cities with higher initial carbon intensity should allocate higher carbon intensity reduction targets (Hao et al., 2015b), such as in Yangzhou and Zhenjiang. According to the Twelfth Five-Year Plan, the targets of carbon intensity reduction (Table 3), are 18% and 19% in Yangzhou and Jinhua. The task allocated to Yangzhou is relatively lower, which is contrary to our result and also the law of development. The current level of carbon intensity should be considered during the process of allocating carbon intensity reduction.

Conditional β-convergence of carbon intensity means that industrial structure has a significant effect on the convergence of carbon intensity. The coefficient of industrial structure is larger than other control variables because industrial structure has a more important effect on the convergence of carbon intensity. Thus, more attention should be paid to industrial structure when setting carbon intensity reduction targets. The goodness of fit ($R^2$) of SEM is larger than that of the panel data models, indicating that spatial factors increase the explanatory power of the convergence models; meanwhile, there are spatial effects across the prefecture-level cities in the YRD. When the reduction tasks of carbon intensity are allocated to different prefecture-level cities with alike carbon intensity, policymakers should also consider the influence of industrial structure, GDP per capita and spatial factors. The higher the economic level is, the more people may care about the environment quality (Hao, Chen, Wei, & Li, 2016; Hao et al., 2015b; Li & Lin, 2015), and the more capital can be used to reduce carbon intensity. The existence of β-convergence of carbon intensity does not necessarily mean that the peak of CO2 emissions would achieve soon. The reducing rate of carbon intensity should be larger than the economic growth rate, thus, low carbon technology and non-fossil energy should continue develop.

Industrial structure reduces the annual growth rate of carbon intensity, consistent with the results of Wang et al. (2016b). The proportion of secondary industries is higher in the YRD, and most are energy intensive, forming the major source of carbon emissions.

### Table 2
Estimation results of β-convergence.

| Regression approach | Absolute convergence | Conditional convergence |
|---------------------|----------------------|-------------------------|
| ln(CI)              | −0.0872***           | −0.0305***              |
| ln(IS)              | −0.0556***           | −0.0035***              |
| ln(PD)              | 0.0119               | 0.0096                  |
| ln(PGDP)            | −0.0305***           | 0.0305***               |
| ln(CI)/ln(IS)       | 0.0976***            | 0.0353***               |
| ln(CI)/ln(PD)       | 0.0262               | 0.0305***               |
| ln(CI)/ln(PGDP)     | −0.3165***           | 0.0305***               |

| λ                   | 0.7920***            | 0.7890***               |
| ρ                   | 0.0912               | 0.0850                  |
| R²                  | 0.1307               | 0.1890                  |
| CorR²              | 0.0444               | 0.0171                  |
| log-likelihood      | 624.8589             | 634.2672                |

Notes: *, **, and *** denote coefficients that are significant at the 10%, 5% and 1% statistical levels, respectively. λ represents the convergence speed. ρ represents the spatial error coefficient. ρ represents the spatial autoregressive coefficient.

### Table 3
The reduction tasks of carbon intensity during the 12th Five-Year Plan (2011–2015).

| Prefecture-level city | Carbon intensity reduce (%) | Prefecture-level city | Carbon intensity reduce (%) |
|-----------------------|-----------------------------|-----------------------|-----------------------------|
| Shanghai              | 19                          | Suqian                | 14                          |
| Nanjing               | 20                          | Hangzhou              | 20                          |
| Wuxi                  | 20                          | Ningbo                | 20                          |
| Xuzhou                | 19                          | Wenzhou               | 19.5                        |
| Changzhou             | 20                          | Jiaxing               | 19.5                        |
| Suzhou                | 20                          | Huzhou                | 20.5                        |
| Nantong               | 18                          | Shaoxing              | 20.5                        |
| Lianyungang           | 18                          | Jinhua                | 19                          |
| Huaiian               | 19                          | Quzhou                | 21                          |
| Yancheng              | 18                          | Zhoushan              | 16                          |
| Yangzhou              | 18                          | Tai’zhou              | 13.5                        |
| Zhenjiang             | 19                          | Lishui                | 15.5                        |
| Taizhou               | 19                          |                       |                             |

Source: The comprehensive work program of energy-saving reduction emission and control for greenhouse gas emissions during Twelfth Five-Year in Shanghai from website http://fgw.jiading.gov.cn/zwdt/ywgz/jnjp/content_122775, Jiangsu from website http://www.js.gov.cn/jsgov/tj/bgt/201302/W02013022525373173900171.doc, Zhejiang from website http://www.zjepb.gov.cn/root14/xsgk/hjtj/201401/P020140109678104789682.pdf.
with relatively higher carbon intensity (Hao et al., 2015a). Industrial transfer has a great impact on carbon intensity, and industrial transformation and upgrading have been executed in the YRD with positive results, decreasing the proportion of secondary industry (Liu & Li, 2015). The government should adjust the industrial structure, reducing the proportion of the secondary industry, increasing the proportion of the tertiary industry (Wang, Fang, & Wang, 2016a). At the meantime, it should be avoid that the higher carbon intensity industries are transferred from YRD to other less developed areas in middle or west China (Li & Lin, 2015; Yang, 2014; Yang, Flower, & Thompson, 2012). Measures should be taken to enhance the supervision of carbon intensity, introduce more low carbon technologies, increase investment in low carbon technologies and provide support for companies that have insufficient budgets for importing advanced technologies. In addition, financial subsidies can be provided to companies that control carbon intensity well.

There is an insignificantly negative relationship between population density and the annual growth rate of carbon intensity, consistent with the results of Zhao et al. (2014). When population density is within a certain range, an increase in population density will reduce the carbon intensity (Zhao et al., 2014). When population density exceeds a certain threshold, the increase in population density will increase the carbon intensity. In some prefecture-level cities of the YRD, the population density is higher, and it may exceed the critical value (Tian, Jiang, Yang, & Zhang, 2011). Considering that each prefecture-level city has a certain population carrying capacity, population density should be controlled to make sure that every person can share public facilities and minimize environmental impact (Yang, 2014).

The interaction effect involving industrial structure is significant, implying that the larger the industrial structure, the lower the speed of convergence to the steady-state level (Brännlund et al., 2015). The result accords with that the higher proportion of the secondary industry, the more difficult to adjust the industrial structure (Hao et al., 2015a).

The impact of interaction effect for GDP per capita shows a significantly negative effect on the annual growth rate of carbon intensity, indicating that the higher the GDP per capita, the higher the speed of convergence to the steady-state level, and it is conductive to decrease the carbon intensity. This is similar as the result of Wang et al. (2016b). The economic level is relatively high in the YRD compared to many areas in China. Additionally, developed prefecture-level cities have more capital and low carbon technology to decrease carbon intensity (Wang et al., 2016b). Therefore, prefecture-level cities should reduce the dependence on coal and optimize the energy structure, but with minimal impact of environment (Yang, Huang, & Thompson, 2014; Yang & Thompson, 2014; Yang, Thompson, & Flower, 2014).

The spatial autoregressive coefficient is significantly positive, indicating that there is an obvious spatial spillover effect of the annual growth rate of carbon intensity across prefecture-level cities in the YRD (LeSage & Pace, 2009). The decreasing annual growth rate of carbon intensity in prefecture-level cities is helpful in decreasing the annual growth rate of carbon intensity in neighboring prefecture-level cities. Meanwhile, the SEM considering spatial factors increases the convergence speed of carbon intensity from 0.0789 to 0.0912, suggesting that considering spatial factors accelerates the convergence rate. The results are similar to the finding of Zhao, Wesley Burnett, and Lacombe (2015). It is important for policymakers to consider spatial factors when setting carbon intensity reduction targets. To reduce carbon intensity, policy intervention in prefecture-level cities should match the policies of neighboring prefecture-level cities. We can set up a low carbon pilot area, summarizing the experiences and lessons of low carbon development to provide references for the development of other regions. Compared to the national average of convergence speed of 0.229 (Hao et al., 2015a), the convergence speed is lower, only 0.1753 in the YRD and the reason is the lower carbon intensity in the YRD.

Comparing this study with other results from China and other countries (Table 4), we found that industrial structure and GDP per capita are important for the convergence of carbon intensity in the YRD, and this is similar as the funding of Hao et al. (2015a). Different from other results, as YRD is in the stage from the medium-term of the industrialization toward post-industrial (Liu & Li, 2015), some high-tech industries were introduced to YRD, which can decrease the carbon intensity.

To our knowledge, the main contribution of the paper is that we made the first analysis of the convergence of carbon intensity across prefecture-level cities utilizing grid data of the YRD. This reveals micro level rules, which offer more accurate information to policymakers, such as that prefecture-level cities with higher carbon intensity should allocate higher targets for reducing carbon intensity. Using grid data analyses in ArcGIS 10.2 and spatial econometric methods offers a new method for analyzing the convergence of carbon intensity. In addition, we investigated the convergence of carbon intensity rather than carbon emissions used by previous scholars. Our investigation provides guidance for the allocation of carbon intensity reductions in the YRD. Furthermore, considering spatial factors, we employed SEM and SLM to analyze the convergence of carbon intensity, finding that a spatial spillover effect is significant in the annual growth rate of carbon intensity across prefecture-level cities in the YRD; the spatial spillover effect accelerates the convergence rate.

Same as most studies, this paper has some limitations. Due to data availability, we chose a study period during 2000–2010. A longer period will be helpful to more accurately estimate the convergence rate of carbon intensity. The convergence rate of carbon intensity can only guide policymakers to roughly allocate carbon intensity, but it cannot allocate carbon intensity concretely. Because prefecture-level cities have different rates of convergence and steady state, it is unavailable for this study to estimate the steady state level in each prefecture-level city. In future study, steady state level of each prefecture-level city could be estimated under new theoretical framework. If data from 2011 to 2015 can be obtained in the future, new studies may provide suggestions for carbon intensity reduction allocations over the Thirteenth Five-Year (2016–2020) Plan.

5. Conclusion

We utilized a balanced panel of prefecture-level cities during 2000–2010 to investigate the convergence of carbon intensity in the YRD. Carbon intensity has been decreasing since 2004. Standard deviation, panel unit root tests and spatial econometric models are utilized to verify σ-convergence, stochastic convergence and β-convergence of municipal carbon intensity. The results indicate that σ-convergence exists during 2000–2002 and 2004–2010, which indicates that the absolute difference in carbon intensity was reduced during 2000–2002 and 2004–2010. Stochastic convergence exists during 2000–2010, which means that the shocks to carbon intensity relative to the average level are only transitory.

The existence of β-convergence can reveal rules that help us disaggregate provincial targets for reducing carbon intensity of prefecture-level cities. The β-convergence means that provinces used to have a similar carbon intensity at the beginning of the period, but the carbon intensity of high carbon intensity prefecture-level cities decreases over time, whereas the carbon intensity of low carbon intensity prefecture-level cities increases over time. The existence of β-convergence can reveal rules that help us disaggregate provincial targets for reducing carbon intensity of prefecture-level cities. The β-convergence means that provinces used to have a similar carbon intensity at the beginning of the period, but the carbon intensity of high carbon intensity prefecture-level cities decreases over time, whereas the carbon intensity of low carbon intensity prefecture-level cities increases over time.
intensity reduction. Prefecture-level cities with higher carbon intensity such as Yangzhou and Zhenjiang should be allocated higher carbon intensity reduction tasks, whereas Zhoushan and Jinhua should be allocated lower carbon intensity reduction tasks. The conditional β-convergence means that we should consider societal and economic conditions when we conduct allocation plans for carbon intensity reduction, such as GDP per capita and industrial structure, the results of interaction effects indicates that different prefecture-level cities converge to different steady states, prefecture-level cities with higher industrial structure converge more slowly, prefecture-level cities with higher population density converge much faster. There is a spatial spillover effect across prefecture-level cities, so we can select a typical city as a low carbon pilot to develop the typical city’s radiation role.

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