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The convergence of Carbon intensity in China at the prefecture-level

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ABSTRACT

Convergence analysis in carbon intensity is a critical tool to decide the CO_2 emission reduction targets. Accurately estimating convergence behavior on a finer scale is generally more effective and practical to address spatial-temporal heterogeneity. However, little research has focused on convergence in carbon intensity across the prefecture-level cities in China. Here, we tested the convergence hypothesis in carbon intensity across 264 prefecture-level cities in China from 1992 to 2013 using convergence analysis, cross-section regressions, and dynamic spatial panel econometric techniques. We also compared different time periods and regions to explore the spatial-temporal heterogeneity of convergence behavior. Findings reveal converging CO_2 intensities across cities and significant spatial effects in this convergence process. In addition, carbon intensity convergence rates for 1992–2013 show an overall decline over time. Furthermore, the analysis of spatial dynamic panel data shows significant conditional β-convergence after controlling for economic growth, population density, urbanization, and finance. We further provide significant evidence that population density, urbanization, and finance had significant negative effects on carbon intensity, while GDP per capita significantly facilitated carbon intensity. By controlling dynamic temporal effects, we find larger long-term, compared to short-term, effects of control variables on carbon intensity. Finally, carbon intensity convergence differs in regional heterogeneity, suggesting the necessity of designing different carbon intensity reduction polices.

Keywords: Carbon intensity; Convergence; Emissions reduction policy; Spatial econometric model; China

1. INTRODUCTION

There is a global consensus that rapid industrialization and accelerating urbanization have fueled unprecedented economic growth and improved the quality of everyday life in China. Whereas they have also boosted China's CO_2 emissions by increasing demand for fossil energy and its consumption over the past four decades [1-3]. Cities are centers of human activity which are estimated to contribute over 80% of all CO_2 emissions in China [4-5]. Thus, the reduction of carbon intensity in urban areas is the fundamental commitment that China will meet its low-carbon targets and peak emission goals.

A growing body of literature attempts to provide quantitative analysis methods for the relationship between economic development and CO_2 emissions to solve the plight mentioned above. Convergence analysis is one of the most commonly used methods. The several advantages of convergence analysis, which can be summarized in the following four points. Convergence analysis provides a description of dynamic changes in CO_2 emissions to support a deeper understanding of the status quo of CO_2 emissions [6]. Convergence analysis offers a more detailed explanation of how CO_2 emissions change in response to economic regulation and low-carbon policies than other analytical methods, such as identifying the factors that drive CO_2 emissions, whereby this helps policymakers to assess the effects of implementing different policies [7]. Rates of convergence indicate the changing trends in CO_2 emissions. When the rate of convergence reaches a specific level, the growth rate of CO_2 emissions in a region with relatively higher CO_2 emissions will decrease or even negative [8]. Finally, convergence analysis offers a theoretical basis for determining equal and fair allocation of obligations and responsibility and enhances prediction accuracy for future CO_2 emissions [9]. Therefore, the convergence analysis of carbon intensity in China's prefecture-level is necessary and crucially important.

This study attempts to investigate the convergence of carbon intensity in a panel of 264 prefecture-level

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cities in China over the period 1992–2013. A detail introduction and formula of the methods used are provided in Section 2. Then section 3 reports the results including the existence of convergence in CO_2 intensity and the main factors that influence change in CO2 intensity.

2. METHODS

The use of convergence analysis for both time series data and spatial data has gradually become more common in investigating energy consumption and CO_2 emissions at multiple scales and over different time periods [1-5]. Thus, we use two types of convergence analysis in this study, stochastic convergence and β-convergence. In addition, we extend the traditional cross-sectional regression model to include the spatiotemporal model to carry out the convergence analysis. The regression models are expressed as follows.

2.1 Stochastic convergence

Stochastic convergence analysis is widely used. We adopt the definition of [10], that stochastic convergence occurs in a prefecture-level city when temporal shocks in carbon intensity disappear from its average level over time.

The literature on convergence indicates that empirical studies frequently use several unit root test, such as the Im-Pesaran-Shin (IPS) panel unit root test [11], the augmented Dickey-Fuller (ADF) test [12], the Levin-Lin-Chu test (Swetnam et al.) and the Phillips and Perron (PP) test [13], to test the stochastic convergence.

2.2 β-convergence

Drawing from conventional neoclassical growth theory, if there is β-convergence in carbon intensity at prefecture-level cities, then carbon intensity at a city with a high level of carbon intensity decreases more rapidly than at a city with a lower level of carbon intensity. The differences in carbon intensity between cities decrease over time, leading to a carbon intensity equilibrium for all cities. There are two types of β-convergence: absolute β-convergence and conditional β-convergence.

(1) Absolute β-convergence

The existence of absolute β-convergence implies that the carbon intensity of each city continues to decline without considering the degree of socio-economic development in a certain city. The process can be represented by:

$$\ln(C_{i,t} / C_{i,t-1}) = \alpha + \beta \ln(C_{i,t-1}) + \varepsilon_{i,t} \quad (1)$$

where $C_{i,t}$ is the carbon intensity of city i in year t, β is the convergence coefficient which denotes the coefficients of the lagged term of carbon intensity, and is an error term. Thus, $\ln(C_{i,t} / C_{i,t-1})$ is the annual growth rate of carbon intensity in year t. α represents a constant term.

(2) Conditional β-convergence

The notion of conditional β-convergence in carbon intensity means that in consideration of certain economic conditions, different cities converge to the equilibrium level of carbon intensity on their path. The process can be represented by:

$$\ln(C_{i,t} / C_{i,t-1}) = \alpha + \beta \ln(C_{i,t-1}) + rX_{i,t-1} + \varepsilon_{i,t} \quad (2)$$

where C, i and t are the same as in Eq. (1), the row vector $X_{i,t-1}$ contains various control variables, and the column vector r denotes the coefficients of the control variables. Other variables are the same as in Eq. (1). If β is statistically significant and negative, then β-convergence can be confirmed.

The rate of convergence β is assumed to be an exponential decay function [14]:

$$\beta = e^{-\tau C} \quad (3)$$

If an estimated coefficient , found by regression, is within the interval (0, 1), then the convergence of carbon intensity to the equilibrium is direct and without oscillation. The parameter is the implied rate of convergence. It can be calculated by the equation:

$$\lambda = -\ln(\hat{\beta}) / \tau \quad (4)$$

where τ is the time interval.

3. RESULTS AND DISCUSSIONS

Figure 1 shows carbon intensity at prefecture-level cities in China for four temporal cross-sections (1992, 2000, 2010 and 2013). The significant spatial disparity has been seen between different regions during the two earlier periods. The hotspot areas with higher values of more than 8 concentrated in the North China, Northeast China, Western China and South China region. The low value areas of less than 3 are widely dispersed in Southwestern China and Central China. In the last two periods, carbon intensity in the hotspot areas decreased significantly. Thus, the phenomenon of spatial heterogeneity turns into a relatively spatial equilibrium. Spatial differences in carbon intensity among regions decreased over the period 1992–2013, which implies that there is spatial convergence across regions. of each prefecture city will tend to be close to the average level of carbon intensity for all cities.

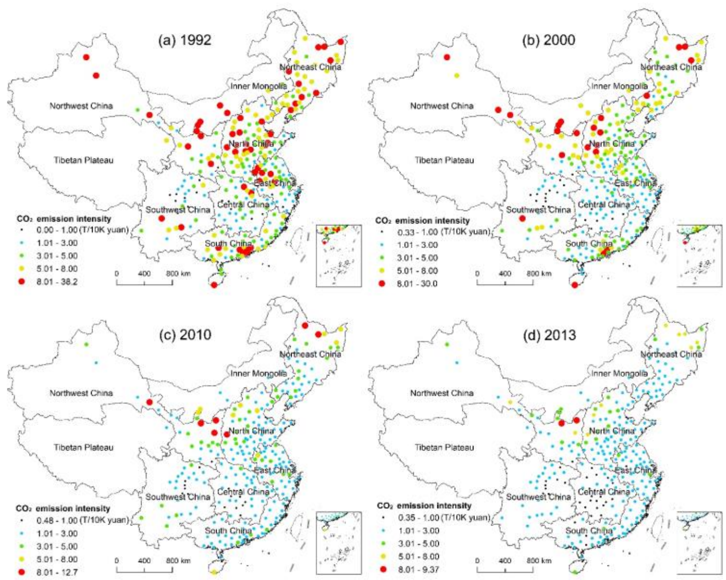

Fig 1 Spatial distribution of carbon intensity in four selected years.

Figure 2 gives an overview of carbon intensity in China and seven subregions from 1992 to 2013. It shows that carbon intensity in the seven subregions decreased over time. The similarity in the results shows that the gaps between different regions had greatly decreased since 1994 and carbon intensity tended to reach an equilibrium level after 2011, especially in northwestern and northern China. This also provides evidence of convergence.

Stochastic convergence indicates that a shock to carbon intensity (relative to the average level of carbon intensity across the whole country) in a specific city is only temporary and short-term shocks disappear over time. It follows from this result that the carbon intensity

One non-spatial and seven spatial cross-sectional regression models (OLS, SAR, SEM, SLX, SDM, SDEM, SAC, and GNS) were used to ensure that we obtained robust estimates of absolute beta-convergence in carbon intensity over the entire sample period (see table.1). Our results provide strong evidence for absolute convergence of carbon intensity. Absolute convergence implies that, if other conditions remain unchanged, prefecture cities with relatively higher carbon intensity in the initial period have more rapidly decreasing rates of carbon intensity, whereby their level of carbon intensity will tend to converge to the same equilibrium as prefecture cities with lower carbon intensity. Our results also indicate that spatial econometric models used in convergence analysis are more appropriate than

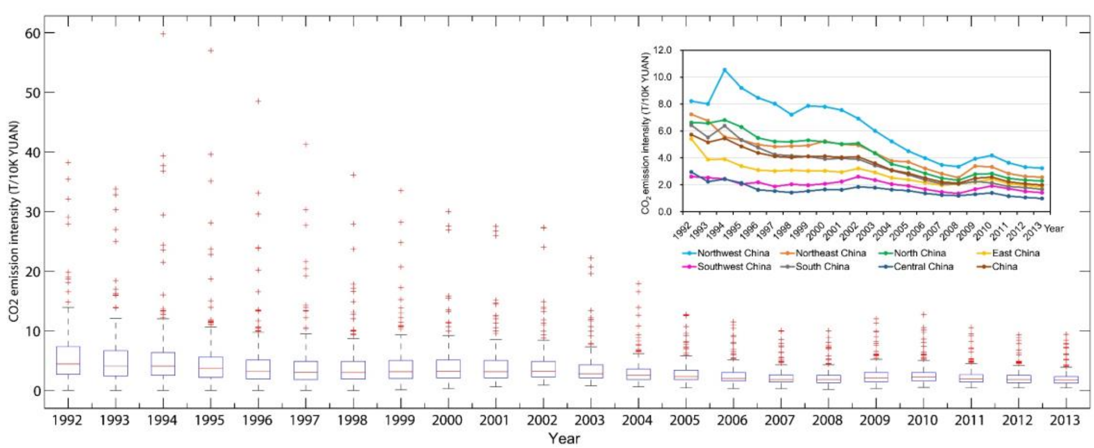

Fig 2 The box and line plots of the carbon intensity in China and seven subregions from 1992 to 2013.

conventional regression models. We were able to investigate spatial absolute convergence and found that prefecture cities with high carbon intensity may affect mechanism of convergence. The results were consistent with our expectations: a city with a comparatively high carbon intensity has a relatively high rate of convergence, and vice versa. The rate of convergence of carbon intensity in north-eastern China was the greatest. Therefore, the result shows that the Northeast Revitalization Strategy has some influence on industrial development as well as reorganization, thus reduces intensive energy use, and increases energy efficiency.

Table 1. Estimation results of cross-sectional regression from 1992 to 2013.

Dep. Var: $\ln(C_t/C_{t-1})$	(1) OLS	(2) SAR	(3) SEM	(4) SLX	(5) SDM	(6) SDEM	(7) SAC	(8) GNS
Constant	0.251^{c}	0.261^{c}	0.441^{c}	- 0.048	- 0.043	0.099	0.197	- 0.051
$\ln(C_{t-1})$	- 0.802^{c}	- 0.799^{c}	- 0.951^{c}	- 0.922^{c}	- 0.952^{c}	- 0.919^{c}	- 0.918^{c}	- 0.979
$W*\ln(C_{t-1})$				0.345^{c}	0.741^{c}	0.225^{c}		0.929^{c}
rho		0.017			0.607^{c}		- 0.238^{c}	0.859^{c}
lambda			0.715^{c}			0.610^{c}	0.746^{c}	- 0.662
Implied convergence speed λ	0.074	0.073	0.137	0.116	0.138	0.114	0.113	0.176
Half-life (year)	9.413	9.500	5.053	5.978	5.008	6.073	6.111	3.950
R^2	0.728	0.728	0.833	0.770	0.837	0.833	0.844	0.870
Log$L$	- 335.2	- 203.1	- 154.3	- 313.0	- 146.2	- 149.7	- 148.6	- 140.8
LM spatial lag	0.074							
robust LM spatial lag	40.821^{c}							
LM spatial error	108.987^{c}							
robust LM spatial error	149.735^{c}							
Direct effects $\ln(C_{t-1})$	- 0.802^{c}	- 0.799^{c}	- 0.951^{c}	- 0.922^{c}	- 0.927^{c}	- 0.919^{c}	- 0.926^{c}	- 0.948
Indirect effects $\ln(C_{t-1})$		- 0.014			0.391^{c}		0.185^{c}	0.593
N	264	264	264	264	264	264	264	264

adjacent prefecture cities.

We used cross-sectional regression with 5-year intervals to investigate the dynamics of absolute convergence, unlike many previous studies. Our results show there is temporal heterogeneity in absolute convergence, and it indicates that the convergence is not stable over time.

Conditional convergence indicates that population density, economic development level, industrial structure, urbanization, and finance play an important role in influencing convergence. Among them, we found that economic development level reduces carbon intensity, which is in line with most previous studies. The estimated coefficient results of other control variables imply that along with rapid urbanization and industrial growth, prefecture-level cities in China will continue to be faced with challenges from the incompatibility of increasing economic development and reducing resource consumption, especially the consumption of fossil fuels. Development and construction in China must therefore depend on taking advantage of renewable and clean energy. The immediate effects of the control variables are significant both in the short term and the long term, whereby their direct and indirect (spillover) effects can increase the spatial effects mentioned above. These results may also be interpreted as the effects of recent shifts in regional development strategies.

We also tested convergence in seven subregions to show regional heterogeneity in rates and influencing

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