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Province-level Convergence of China CO_2 Emission Intensity:

A Spatial Dynamic Panel Data Analysis

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Abstract

This study offers a unique contribution to the literature by investigating the convergence of province-level carbon dioxide emission intensity among a panel of 30 provinces in China over the period 1990-2010. We use a novel, spatial dynamic panel data model to test the hypotheses of absolute beta convergence and conditional beta convergence. Our results suggest: (1) CO_2 emission intensities are converging across provinces in China; (2) the rate of conditional beta convergence is higher than the rate of absolute beta convergence; (3) province-level CO_2 emission intensities are spatially correlated, and the rate of convergence, when controlling for spatial autocorrelation, is higher than with the non-spatial models; and, (4) the rate of convergence is affected by the ratio of coal consumption to total energy consumption, secondary industry output value to the total industry output value, and province-level energy intensity.

Keywords: CO_2 emission intensity, Convergence, Spatial dynamic panel data, China

JEL codes: C40, Q4, Q54, Q56, R11

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1 INTRODUCTION

Understanding the distribution of carbon dioxide emissions (CO_2) through time and space can help policy makers in designing policies to combat climate change. The geographic distribution of CO_2 emissions does not affect the global climatic impact, but it does affect the political economy of negotiating multilateral agreements (Aldy, 2006). If the People's Republic of China were to formulate a national climate change policy or agree to ratify an international agreement such as the Kyoto protocol then it must begin to look inward to determine the sources and distribution of emissions. With this look inward, policy makers may be interested in determining how the distribution of province-level emissions is changing over time. That is, do interregional differences in emission levels tend to disappear or increase over time? If the differences diminish over time (and we observe a decrease in the overall growth rate compared to some base year), then policymakers may be less worried about such a mitigation scheme. If, on the other hand, the differences tend to perpetuate over time (i.e., high emitting provinces remain high emitters now and in the future) then policymakers may want to enact policies to reduce emissions.

Other than the fact that a national carbon mitigation scheme may come at the expense of economic growth, one of the reasons perhaps that China has been slow to adopt such a scheme is due to uncertainty in province-level abatement costs. For example, if a province is currently a high emitter then arguably its marginal cost of reducing a unit of CO_2 should be relatively low, whereas a low-emitting province arguably would have higher relative marginal costs for reducing another unit. In the U.S., policy regimes often ignore location and dispersion characteristics of the sources of emissions, and emissions are penalized at a single permit price (Fowlie and Muller, 2013). Fowlie and Muller (2013) argue that in the presence of uncertainty in abatement costs, differentiated policies may improve welfare. Therefore, this study seeks to explore these differentiated policies in the context of provinces in China whose emissions are converging through time.

Global climate change is an international problem in scope, yet domestic or regional policies can be implemented to mitigate CO_2 emissions. With the "Copenhagen Accord Submission," China set the goal to reduce carbon intensity by 40-45% by 2020, compared to 2005 emission levels. The Chinese government regards a reduction in CO_2 emission intensity as a desirable way of limiting the incremental environmental damages associated with rapid economic growth. Although CO_2 emission intensity has been decreasing year by year in China, it still has a long way to go to achieve its reduction goal. These reductions are expected to be achieved through improvements in energy efficiency, and reductions in energy consumption.

Compared to previous studies, this study offers two unique contributions to the literature: (1) by testing the beta (β) convergence hypothesis through the use of a novel, dynamic spatial data model; and (2) by more explicitly considering the different types of spatial dependence within the data using newly developed spatial autocorrelation post-estimation tests.

It is difficult to compare total carbon dioxide emissions across provinces because of the variation in their size and economic activity, so we instead analyze province-level emission intensities. Emission intensity, which is simply the ratio of overall province emissions to province-level gross domestic product, normalizes emissions across provinces to offer a more compatible apples-to-apples comparison. From a policy sense, an analysis of emission intensity offers a more equitable measure for negotiating multilateral agreements. To further analyze the convergence of emissions we condition the growth rates of emissions on certain structural and non-structural factors, which include population size, the ratio of coal consumption to total energy consumption, the ratio of secondary industry output value to total industry output value, and energy intensity.

In this study, we test for conditional β-convergence among a panel of provinces in China using a newly developed spatial, dynamic panel data model (SDPD). We find that there is indeed positive spatial autocorrelation among provinces which suggests that the SDPD model should provide more efficient estimates of the speed of convergence. Based on the estimation results, we find evidence that (1) CO_2 emission intensities are converging among the provinces in China; (2) the rate of conditional β-convergence is higher than the rate of absolute β-convergence, and the estimated rate of convergence is higher with the SDPD model than with the non-spatial models; and, (3) the rate of convergence is affected by the ratio of coal consumption to total energy consumption, the secondary industry output value to the total industry output value, and province-level energy intensity.

The rest of this paper is structured as follows. Section two offers a brief literature review and description of the notion of convergence. Section three introduces the data and methodology. Section four discusses the estimation results. Finally, section five concludes this study and offers some policy suggestions.

2 BACKGROUND

2.1 Literature Review

The study of regional convergence dynamics of per-capita income stems from the early theoretical work of Solow (1956) and Swan (1956), and the empirical framework was later developed by Mankiw et al. (1992) and Barro and Sala-i-Martin (1991, 1992; 1995). This framework led to the β-convergence approach, which is an empirically testable hypothesis that historically has been used to examine the inverse relationship between growth in per-capita income (or gross domestic product) over time against the initial level of per-capita income. Here we expand this approach to examine the convergence of emission intensities among a panel of provinces in China.

A large number of past studies have examined the factors which have led to the decline in CO_2 emission intensity. For example, Liddle (2010) found that improvements in technology, changes in the country's economic structure and energy efficiency accounted for most of the decline. Gonzalez and Martinez (2012) found that the energy intensity effect was the driving factor behind the main decreases of CO_2 intensity. Ma et al. (2012) found that both the adjustment in economic structure and the decline in secondary industry's CO_2 emission intensity can influence China's CO_2 emission intensity in an independent way (Liddle, 2010; Gonzalez and Martinez, 2012; Ma *et al.*, 2012). However, an examination as to whether the differences in CO_2 emission intensity diminish over time, resulting in convergence, has received little attention among economists.

Spatial dependence is an important factor in regional convergence. The preponderance empirical evidence on regional β-convergence is based almost exclusively on cross-sectional or panel data models without spatial effects. As is well known by know, regional data cannot be regarded as spatially independent because of the presence of similarities among neighboring regions, and as a result models without spatial effects may lead to biased or inefficient estimates of the rate of convergence (Arbia *et al.*, 2005). Further, if the growth rates of the poor regions are higher than the growth rates of the rich regions, the spatial inequality may decrease over time, which may result in convergence (Gezici and Hewings, 2007). Even though the neoclassical model assumes perfect mobility of factors of production between economies, there may be significant adjustment costs or barriers to mobility for labor and capital. In cases where regions pursue their own growth promoting policies, there may be spillover effects from those regions to the adjacent regions (Anselin, 1998). Thus, incorporating spatial effects into the analysis may significantly impact the rate of convergence across regions.

2.2 Convergence Hypothesis

The concept of convergence in the most general sense is that the inequality in economic growth between countries or regions should decrease over time. However, convergence is not restricted to the economic growth literature alone, and has been applied recently to other fields, including energy economics (Ezcurra, 2007a, b; Duro *et al.*, 2010; Ma and Oxley, 2012; Herrerias and Liu, 2013). Different notions of convergence are linked to different methodological approaches. Three well-known convergence hypotheses include that of sigma convergence, absolute beta convergence, and conditional beta convergence. These notions have been tested empirically, initially with cross-sectional data and then later with panel data.

Other notions of convergence include stochastic convergence, which implies that the difference in long-run forecasts of income between two economies approaches zero over time. Club convergence hypothesizes that the per-capita income of countries or regions, with similar structural characteristics and initial levels of income, converge to multiple equilibriums in the long-term.

In this paper, we abstract away from stochastic and club convergence and instead use the two more prominent tests in the literature: sigma and beta convergence. Each of these concepts is outlined in the next section.

2.2.1 Sigma Convergence

The sigma convergence approach became popular the seminal work of Quah in the early 1990s (Quah, 1993; Quah, 1996). Sigma convergence pertains to the decline in the cross-sectional dispersion of per capita incomes over time. As suggested by Quah (1993), sigma convergence determines whether or not the distribution of income across economies is becoming more equitable over time (Quah, 1993).

Sigma convergence has attracted much attention in the regional science and economic geography literature (Barro and Sala-i-Martin, 1991; Bernard and Durlauf, 1996; Quah, 1996). Several different measures have been employed to examine this form of convergence including the sigma coefficient, the coefficient of variation, and so on. The formulas of the measures are as follows:

(1) Sigma Coefficient (σ): $\sigma = \sqrt{[\sum_i (\ln Y_i - \overline{\ln Y})^2]/N}$

(2) Coefficient of Variation (V): $V = \frac{S}{Y}$, $S = \sqrt{[\sum_i (Y_i - \overline{Y})^2]/N}$,

where Y_i denotes the CO_2 emission intensity of province *i*, and $\overline{Y}$ is the average CO_2 emission intensity of all provinces, *N* is the total number of provinces, and *S* is the standard deviation.

2.2.2 Beta Convergence

Beta convergence is defined as a negative relationship between the initial income level and subsequent income growth rate. This concept implies that poorer economies should grow faster than richer ones. We apply this same concept to the convergence of emission intensities.

Beta convergence includes absolute beta convergence and conditional beta convergence. The absolute beta convergence assumes that all economies converge to the same unique and global steady-state equilibrium regardless of the initial conditions. In our study, an estimation method for this type of model would only include the initial level emission intensity as an explanatory variable.

In the case of conditional beta convergence, equilibrium differs by economy, and each particular economy approaches its own but unique equilibrium. In other words, the empirical findings should suggest the existence of convergence conditional on the initial level of emission intensity and other structural variables. Thus, conditional beta convergence may be proper specification if the estimation results of the absolute beta convergence hypothesis are not valid.

Beta convergence analysis has generally been employed in order to investigate convergence across economies or regions. There are two models general used in the literature: non-spatial, dynamic panel date models (Islam, 1995; Ezcurra *et al.*, 2007; Lopez-Rodriguez, 2008) and spatial, cross-sectional models (Fan and Casetti, 1994; Rey and Montouri, 1999; Ezcurra *et al.*, 2007). Regional scientists often posit that the rates of economic growth are interdependent across regions due to (economic) spillover effects (Conley and Ligon, 2002); therefore, a spatial, dynamic panel data framework seems appropriate because it controls for both time-invariant heterogeneity across regions and spatial autocorrelation. Thus, incorporating spatial effects into the dynamic panel data model may lead to more efficient estimates of the rate of convergence across provinces.

3 DATA AND METHODOLOGY

3.1 Data

This paper uses a panel data of China's 30 provinces and municipalities for the period 1990-2010 (Hong Kong, Macao, Taiwan and Tibet are not included due to lack of data). The

Chinese Statistical Yearbook (CSY) and Chinese Energy Statistical Yearbook (CESY) have the annual data on energy consumption and gross domestic products for all the provinces and municipalities (CESY, 1991; CSY, 1991). But it is lack of the data of CO_2 emissions. In this paper, we estimate the CO_2 emissions for each province by following the IPCC Guidelines (Intergovernmental Panel on Climate Change, 2006) (IPCC, 1996). These data were then used to calculate the units of CO_2 emission per unit GDP, which defines CO_2 emission intensity. We also have values of other variables such as: population, the ratio of coal consumption to total energy consumption, the ratio of secondary industry output value to total industry output value and energy intensity since 1990. These variables will be used as the exploratory variables when we calculate the conditional beta convergence. The data descriptive statistics are shown in Table 1.

Table 1. Descriptive Statistics

Variable	Description	Mean	Median	Max	Min	SD
CI_t	Carbon dioxide emission intensity (tonne/10K Yuan)	4.050	3.280	15.750	0.540	2.650
CI_{t-1}	Carbon dioxide emission intensity (tonne/10K Yuan)	6.530	4.990	27.950	1.110	4.920
POP	Population (Million)	40.640	37.250	94.880	4.480	24.780
RCC	The ratio of coal consumption to total energy consumption	0.680	0.690	0.930	0.290	0.150
RSI	The ratio of secondary industry output value to total industry output value	0.430	0.430	0.650	0.200	0.080
EI	Energy Intensity (tce/10K Yuan)	2.990	2.240	10.970	0.580	2.200

Notes: Max, Min and SD denote the maximum value, minimum value, and standard deviation, respectively.
The data is four five years periods from 1990 to 2010 for 30 provinces and municipalities in China. N = 120.

3.2 Regression Model

The traditional cross-section model assumes that all regions or economics under consideration have the same steady state income path. But this is a highly restrictive assumption and may induce significant heterogeneity bias in estimates of convergence coefficient. As Quah (1993) points out traditional cross-section approach does not reveal the dynamic of the growth processes. So in this paper, we would like to apply the dynamic panel data approach to estimate the convergence coefficient. The general econometric specification of a dynamic panel data model is given as follows:

$$\ln(Y_{it} / Y_{i,t-\tau}) = \beta \ln(Y_{i,t-\tau}) + A \ln(X_{i,t-\tau}) + \mu_i + \varepsilon_{it} \tag{3}$$

where Y_{it} denotes the dependent variable (CO_2 emission intensity) for province i at time t ($i = 1,...,N; t = 1,...,T$). X_{it} is a matrix of observations on the explanatory variables, which includes population, the ration of coal consumption to total energy consumption, the ratio of secondary industry output value to total industry output value and energy intensity in this case. The parameter μ_i denotes the individual effect for each province. The parameter A is a column vector of regression coefficients; the parameter $\beta = -(1 - e^{-\gamma\tau})$, a negative value of β signifies the beta convergence; τ is the year interval, and γ is the rate of convergence, which can be calculated as:

$$\gamma = -(\ln(1 + \beta)) / \tau \tag{4}$$

Even though the dynamic panel data could reveal the dynamic growth process, there may be spillover effects from one region to the adjacent regions. Such as the technological diffusion and environmental policies may follow a spatial pattern as regions may have different capacities to create or absorb new technologies and policies. So, we would like to observe the spatial autocorrelation and spatial effects in the following analysis.

3.3 Spatial Analysis

3.3.1 Spatial Autocorrelation of Moran's I

Up to now, various indices are used for measuring spatial autocorrelation, such as Moran's I, Geary's and Global G, etc., where "Moran's I" is the one most commonly used. The formula of Moran's I is given as follows:

$$(5) \qquad Moran's\ I = \frac{\sum_i \sum_j \omega_{ij}(Y_i - \bar{Y})(Y_j - \bar{Y})}{S^2 \sum_i \sum_j \omega_{ij}}; \quad S^2 = \frac{1}{n}\sum_i (Y_i - \bar{Y}); \quad \bar{Y} = \frac{1}{n}\sum_i Y_i$$

where Y_i and Y_j represent CO_2 emission intensity of province i and j, respectively. The term ω_{ij} denotes the element in the i^{th} row and j^{th} column of the spatial weight matrix. In this study, we choose the binary contiguity matrix, which is determined by observing whether the regions share a common border. The elements of the spatial weight matrix are defined as: if two regions i and j are neighbors, then the matrix elements $\omega_{ij} = 1$ and $\omega_{ij} = 0$ otherwise. Consistent with the literature, we normalize the spatial weight matrix according to row standardization (LeSage and Pace, 2009). That is, the sum of elements ω_{ij} in each row equals one. Row standardization allows us to interpret spatial spillover effects as an average of all neighbors.

In this study, we observe the Moran's I value for each five year intervals. The results in Table 2 indicate positive and statistically significant spatial correlation for each period. This indicates that China's carbon dioxide emission intensity tend to cluster together. Specifically, the provinces with high carbon dioxide emission intensities have a tendency to cluster together, whereas the provinces with low carbon dioxide emission intensities cluster together. So, we would like to posit a dynamic spatial panel data model to analyze the convergence since the spatial autocorrelation among the provinces implies that standard ordinary least squares (OLS) regression may lead to significant bias in regression results.

Table 2. Moran's I Index of Carbon dioxide emission intensity and its significance

	1991-2010	1991-1995	1996-2000	2001-2005	2006-2010
Moran's I	0.394	0.450	0.389	0.274	0.205
Z-Statistic	3.650	4.129	3.607	2.630	2.034
P-value	0.000	0.000	0.000	0.008	0.042
Significant level	***	***	***	***	**

Notes: The symbols ***, **, * denote a significance level of one, five and ten percent, respectively.

3.2.2 Dynamic Spatial Econometric model

As we mentioned above, it is important to investigate the spatial patterns that may indicate the spillover effects among regions. Spatial dependence can be handled in beta convergence in alternative ways (Elhorst, 2010); the grouped equation can be represented as follows:

$$\begin{aligned} \ln(Y_{it}/Y_{i,t-\tau}) &= \rho\sum_{j=1}^{N}W_{ij}\ln(Y_{it}/Y_{i,t-\tau}) + \beta\ln(Y_{i,t-\tau}) + A\ln(X_{i,t-\tau}) \\ &\quad + \sum_{j=1}^{N}W_{ij}[\ln(Y_{i,t-\tau}) + \ln(X_{ij,t-\tau})]\theta + \mu_i + \phi_{it} \\ \phi_{it} &= \lambda\sum_{j=1}^{N}W_{ij}\phi_{it} + \varepsilon_{it}, \end{aligned} \tag{6}$$

where ρ denotes the scalar spatial autoregressive parameter on the dependent variable, λ denotes the spatial autocorrelation coefficient on the error term, and θ is a (K×1) vector of spatial autocorrelation coefficients on the explanatory variables. The error term, ε_{it}, is assumed to be independently and identically distributed with a zero mean and variance σ^2.

The term $\rho\sum_{j=1}^{N}W_{ij}\ln(Y_{it}/Y_{i,t-\tau})$ denotes the interaction effect of the dependent variable $\ln(Y_{it}/Y_{i,t-\tau})$ with the dependent variables $\ln Y_{jt}/Y_{j,t-\tau}$ in neighboring provinces, where W_{ij} is the *i,j-th* element of a pre-specified nonnegative (N×N) spatial weighting matrix *W*. $\sum_{j=1}^{N}W_{ij}\ln(X_{ij,t-\tau})$

denotes the weighted average effects of the neighboring provinces on the independent variables; and $\sum_{j=1}^{N} W_{ij}\phi_{it}$ denotes the weighted average effects of the neighboring provinces on the error terms.

The restriction of the parameters within Equation (6) defines the specific type of spatial panel model used. Principally, there are four different types of spatial panel data models. One, the spatial autoregressive model (SAR) is obtained by restricting both $\theta = 0$ and $\lambda = 0$ – this model exhibits spatial dependence within only the dependent variable. Two, the spatial error model (SEM) is obtained by restricting both $\rho = 0$ and $\theta = 0$ – this model exhibits spatial dependence within only the error terms. Three, the spatial cross-regressive model (SCR) is obtained by restricting $\rho = 0$ and $\lambda = 0$ – this model exhibits spatial dependence within only the independent variables. Four, the spatial Durbin model (SDM) is obtained by restricting $\lambda = 0$ – this model allows for spatial dependence within both the dependent variable and the independent variables. Finally, if all the parameters with the exception of β are restricted, then the model reduces to the traditional panel data model with two-way fixed effects.

Using Likelihood Ratio test, the SDM model can be tested to determine whether it can be simplified to the SAR, SEM, or SCR model (LeSage and Pace, 2009). The three hypothesis tests are

(7) $$H_{01}: \theta = 0;$$

(8) $$H_{02}: \theta + \rho\beta = 0;$$

(9) $$H_{03}: \rho = 0;$$

Equation (7) examines whether the spatial Durbin model can be simplified to the spatial lag model; equation (8) examines whether it can be simplified to the spatial error model; and, equation (9) examines whether the spatial Durbin model can be simplified to the spatial cross-regressive model. All tests follow a chi-squared distribution. A rejection of all hypotheses suggests that the spatial Durbin model provides the best fit to the data.

4 ESTIMATION RESULTS

In this study, by using the panel data regression rather than the cross sectional regression, we divide the sample into several short time spans. As Islam (1995) argued, a short time span will make the short term disturbances large. Additionally, by considering the spatial effects, a shorter time span, such as one or two year span is also inappropriate because the spillover effects, such as the technological spillovers might take several years to happen. Hence, we will follow 5 year spans as is done in Islam's (1995) use of the dynamic panel data approach and also according to the "Five-Year Plans" of China. That is, $\tau = 5$, so we use the data of the corresponding year 1990, 1995, 2000, 2005 and 2010.

4.1 Results of Sigma Convergence

As we mentioned in the notion of sigma convergence, there are several different measures could be used to estimate it. In this paper, we use both the coefficient of variation and sigma coefficient to estimate the sigma convergence from 1990 to 2010. We draw the initial and end points of each "Five-Year Plans" period. The results are shown in Figure 1.

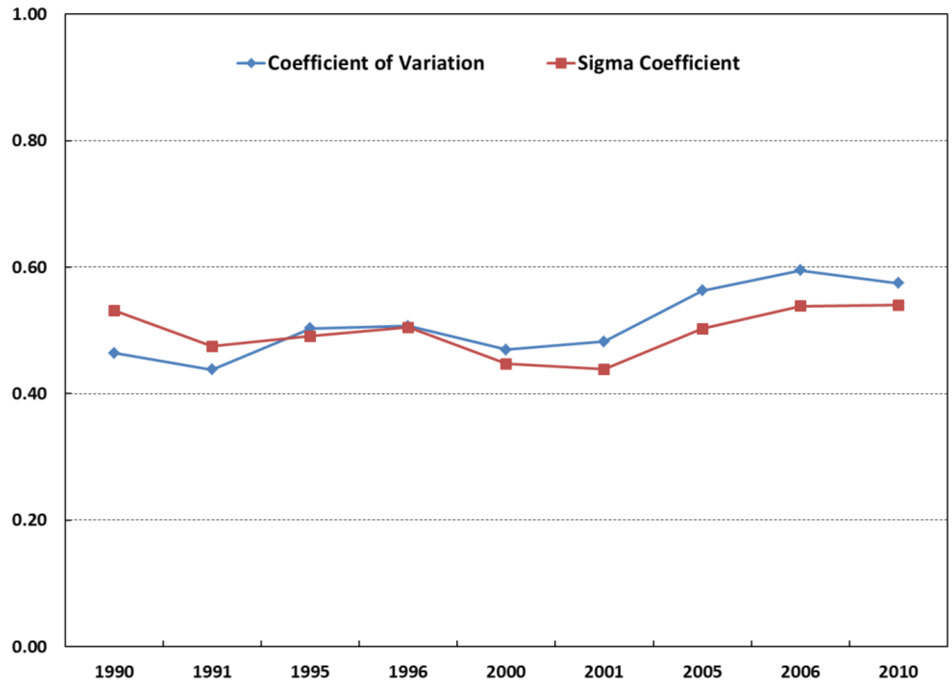

Figure 1. Coefficient of Variation and Sigma Coefficient

From this figure, we can find that the change trends of provincial CO_2 emission intensity are similar with both measures. During the "Eighth-Five Year Plan" (1991-1995) and the "Tenth-Five Year Plan" (2001-2005), the coefficients are shown as increase trend, and during the "Ninth-Five Year Plan" (1996-2000) and the "Eleventh-Five Year Plan" (2006-2010), the coefficients are shown as decrease trend. Even though the change trend of each period is stable, the change trend of the overall period is not stable and do not gradually reduce, so we could not get the exact result of sigma convergence in this case.

4.2 Empirical Results of Absolute Beta Convergence

In equation (3), if we set $A = 0$, then we have the equation to calculate the absolute beta convergence, which is shown as below:

(10) $$\ln(Y_{it} / Y_{i,t-\tau}) = \beta \ln(Y_{i,t-\tau}) + \mu_i + \varepsilon_{it}$$

If we incorporate the spatial econometric model into the above equation, then we have the spatial econometric equation of absolute beta convergence test as

$$\begin{aligned} &\ln(Y_{it}/Y_{i,t-\tau}) = \rho\sum_{j=1}^{N} W_{ij}\ln(Y_{it}/Y_{i,t-\tau}) + \beta\ln(Y_{i,t-\tau}) + \sum_{j=1}^{N} W_{ij}\ln(Y_{i,t-\tau})\theta + \mu_i + \phi_{it} \\ &\phi_{it} = \lambda\sum_{j=1}^{N} W_{ij}\phi_{it} + \varepsilon_{it}, \end{aligned} \tag{11}$$

Before we continue to estimate the absolute beta convergence, we conduct a Hausman test to test the correct panel data specification between fixed effects and random effects. The Hausman test results (12.4680, with 3 degrees of freedom, $p < 0.01$) imply that the fixed effects model is the more appropriate specification.

The results of absolute beta convergence by using the spatial dynamic panel data model where we include the spatial effects are summarized in Table 3. From the results, we can find that the coefficients of $\ln(Y_{i,t-\tau})$, β are negative and statistically significant at one percent level under each model specification. It implies that the absolute beta convergence of provincial level carbon dioxide emission intensity exists in China.

From the results, we can also find that the spatial effect is significant since ρ and λ are positive and statistically significant. So we have the conclusion that spatial model is more appropriate than non-spatial model. So we continue to perform the Likelihood Ratio (LR) test to test the three hypothesizes from equation (7) to equation (9). According to the LR test results, the SAR, SEM and SCR models are rejected in favor of the SDM model. The results of these tests are provided in the Appendix in section 1. These results imply that the spatial Durbin model is the most appropriate specification model.

Table 3. Estimation Results of Absolute Beta Convergence of CO_2 Emission Intensity

Determinants	OLS	SAR	SEM	SCR	SDM
$\ln(Y_{t-\tau})$	-0.3121*** (-8.0566)	-0.2454*** (-4.5551)	-0.3929*** (-5.9684)	-0.5856*** (-5.8268)	-0.6141*** (-5.8973)
$W^*\ln(Y_{t-\tau})$	NA	NA	NA	0.3147*** (2.9342)	0.4671*** (4.0262)
ρ	NA	0.2890** (2.6512)	NA	NA	0.4509*** (4.5630)
λ	NA	NA	0.4730*** (4.8826)	NA	NA
Implied Υ ($\beta = -1+ e^{-5\Upsilon}$)	0.0748	0.0563	0.0998	0.1762	0.1904
σ^2	0.0497	0.0603	0.0537	0.0467	0.0499
R^2	0.4666	0.5105	0.4471	0.5028	0.5950
Sample	120	120	120	120	120
Log Like	10.3497	11.9990	16.7329	14.5731	21.4826

Note: All variables are measured as natural logs. The symbols ***, ** and * denote a one, five and ten percent significance level, respectively. Numbers in the parentheses represent t-test values.

By using the five year spans for the period of 1990-2010, we can find that the rate of absolute beta convergence with OLS model is 0.0748 (7.48%), and the rate of absolute beta convergence with SAR, SEM, SCR and SDM models are 0.0563(5.63%), 0.0998 (9.98%), 0.1762 (17.62%) and 0.1904 (19.04%), respectively. Except the SAR model, the estimates of convergence rate of all other spatial models are higher than the OLS model. And the highest convergence rate is from the SDM model, which is the most appropriate model that we concluded above.

4.3 Empirical Results of Conditional Beta Convergence

With the estimation of conditional beta convergence, we add the population, the ratio of coal consumption to total energy consumption, the ratio of secondary industry output value to total industry output value and energy intensity as the explanatory variables into the equation.

We also conduct the Hausman test as the same with absolute beta convergence analysis to test the fixed effects vs. the random effects. The Hausman test results (36.8974, with 11 degrees of freedom, $p < 0.01$) also imply that the fixed effects model is the more appropriate specification with the conditional beta convergence analysis.

The estimation results of conditional beta convergence of carbon dioxide emission intensity are summarized in Table 4. From the results, we can also find that the coefficient of $\ln(Y_{i,t-\tau})$, β are negative and statistically significant at one percent level under each model specification. So we could conclude that the conditional beta convergence of provincial level carbon dioxide emission intensity also exist in China.

Table 4. Estimation Results of Conditional Beta Convergence of CO_2 Emission Intensity

Determinants	OLS	SAR	SEM	SCR	SDM
$\ln(Y_{t-\tau})$	-0.7590*** (-5.7600)	-0.7900*** (-5.8218)	-0.8596*** (-7.0186)	-0.8374*** (-6.2703)	-0.8750*** (-6.4552)
ln(POP)	-1.1172** (-2.3573)	-0.9843** (-2.0224)	-0.8985* (-1.8831)	-0.7779 (-1.5225)	-0.7153 (-1.3815)
ln(RCC)	-0.5322*** (-2.6570)	-0.5275** (-2.5640)	-0.5146** (-2.5634)	-0.4888** (-2.4669)	-0.4834** (-2.4076)
ln(RSI)	0.0618 (0.2961)	0.1895 (0.8784)	0.5140** (2.2596)	0.5754** (2.3576)	0.6493*** (2.6115)
ln(EI)	0.3924*** (2.6516)	0.5445*** (3.5696)	0.5071*** (3.6581)	0.3634** (2.1602)	0.4015** (2.3524)
ρ	NA	0.4120*** (4.3512)	NA	NA	0.4280*** (4.2786)
λ	NA	NA	0.5490*** (6.2151)	NA	NA
$W*\ln(Y_{t-\tau})$	NA	NA	NA	0.4079 (1.4689)	0.6230** (2.1663)
W*ln(POP)	NA	NA	NA	-1.1497 (-0.9428)	-0.0027 (-0.0022)
W*ln(RCC)	NA	NA	NA	-0.2159 (-0.5911)	0.1825 (0.4894)
W*ln(RSI)	NA	NA	NA	-1.8343*** (-4.4438)	-1.2957*** (-3.0862)
W*ln(EI)	NA	NA	NA	-0.5100* (-1.7072)	-0.4425 (-1.4602)
Implied ϒ ($\beta = -1+e^{-5\Upsilon}$)	0.2846	0.3121	0.3927	0.3632	0.4159
σ^2	0.0417	0.0440	0.0389	0.0366	0.0376
R^2	0.5673	0.6429	0.5462	0.6366	0.6947
Sample	120	120	120	120	120
Log Like	22.9091	29.6036	34.5804	33.3162	38.7875

Note: All variables are measured as natural logs. The symbols ***, ** and * denote a one, five and ten percent significance level, respectively. Numbers in the parentheses represent t-test values.

Since we also find that ρ and λ are positive and statistically significant in the conditional convergence estimation, we will do the LR tests to test the three hypothesizes again. The results imply that the SDM model is still the most appropriate specification model with the conditional beta convergence model. The results are provided in the Appendix in section 2.

From the results, we can find that the rates of conditional beta convergence are relatively higher than the rates of absolute beta convergence with each respective model. For instance, the rate of conditional beta convergence with OLS model is 0.2846 (28.46%) while the rate of absolute beta convergence with OLS model is 0.0748 (7.48%). And the rate of conditional beta convergence with SAR, SEM, SCR and SDM models are 0.3121 (31.21%), 0.3927 (39.27%), 0.3632 (36.32%) and 0.4159 (41.59%), which have the same feature as OLS model. So we can conclude that the convergence rate is higher when we consider the initial conditions of the provinces. With the conditional beta convergence, we can also find that the convergence rate with considering the spatial effects is much higher.

The regression results also suggest that the ratio of coal consumption to total energy consumption, the secondary industry output value to the total industry output value and the energy intensity are statistically significantly affect the growth rate of CO_2 emission intensity, which further affect the convergence rate of the provincial level CO_2 emission intensity.

5 CONCLUSION AND POLICY IMPLICATIONS

In this paper, we analyzed the provincial convergence of CO_2 emission intensity in China. We proposed a spatial dynamic panel data model that the spatial spillovers are introduced into the pure dynamic panel data model. By using this SDPD model, we can avoid the omitted variable bias involving cross sectional equations and pure dynamic panel data equations.

Our empirical results suggest that: (1) the provincial convergence of CO_2 emission intensity exists in China; (2) the rate of conditional beta convergence is higher than the rate of absolute beta convergence; (3) the provincial CO_2 emission intensities are spatially correlated and the rate of convergence with considering the spatial effects is higher; (4) the ratio of coal consumption to total energy consumption, the secondary industry output value to the total industry output value and the energy intensity are statistically significantly affect the convergence rate.

The finding of the provincial convergence of CO_2 emission intensity imply that the provinces with low CO_2 emission intensity and the provinces with high CO_2 emission intensity have the trend to convergence to the same equilibrium with the factors of economic development, technology improvement and so on. The provincial disparity of CO_2 emission intensity is gradually shrinking over time. This result suggests the Chinese government should implement the policy to reduce emission intensity as well as the economic development.

The finding of a higher rate of conditional beta convergence and a higher rate of spatial models actually call for more policy activism. In order to decrease the steady state level of provincial CO_2 emission intensity, provinces were to focus only on the rates of emission and economic growth. However, all the tangible and intangible factors may enter into their respective individual effects. Improvements in these factors may have direct positive effects on the province's long-run emission intensity level. Since the ratio of coal consumption to total energy consumption, the secondary industry output value to the total industry output value and the energy intensity are statistically significantly affect the convergence rate, the policy suggestions will be encouraging the development of less carbon-intensive energy resources such as natural gas or renewables to replace the coal consumption and promoting the improvement of overall energy efficiency.

The spatial autocorrelation and higher convergence rate of spatial models exist in both absolute beta convergence model and conditional beta convergence model, which implies that the finding of spatial autocorrelation in the growth rates is not an artifact of the convergence relationship since there remains strong spatial dependence after conditioning on the initial CO_2 emission intensity. This result also suggest that, while provinces may be converging in relative steady state equilibrium, they do not do so independently but rather tend to display movements similar to their regional neighbors. Under the spatial dynamic panel data model, provinces may additionally focus on learning from neighbors. This suggests that the Chinese government should promote the sharing and exchange of information and technology across provinces, and develop appropriate policies to strengthen cross province development.

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APPENDIX

A.1. Likelihood Ratio (LR) tests of absolute beta convergence model

According to the LR test results (18.9666, with 1 degree freedom, $p < 0.01$), the null hypothesis (7) that the SDM model can be simplified to the SAR model is rejected at a one percent significant level. Similarly, the null hypothesis (8) and hypothesis (9) that the SDM model can be simplified to the SEM model and the SDM model can be simplified to the SCR model are also rejected at a one percent level based on the LR test results (9.4993, with 1 degree freedom, $p < 0.01$) and (13.8190, with 1 degree freedom, $p < 0.01$). These results imply that the spatial Durbin model is the most appropriate specification model.

A.2. Likelihood Ratio (LR) tests of conditional beta convergence model

According to the LR test results (18.3677, with 5 degree freedom, $p < 0.01$), the null hypothesis (7) that the SDM model can be simplified to the SAR model is rejected at a one percent significant level. Similarly, the null hypothesis (8) and hypothesis (9) that the SDM model can be simplified to the SEM model and the SDM model can be simplified to the SCR model are also rejected at a five percent level based on the LR test results (8.4141, with 5 degree freedom, $p < 0.05$) and (10.9425, with 5 degree freedom, $p < 0.05$). These results imply that the spatial Durbin model is the most appropriate specification model.