Province-level Convergence of China CO_2 Emission Intensity

Xueting Zhao
Ph.D. Candidate, Division of Resource Management
West Virginia University
Morgantown, WV, 26505-6108
Email: Xueting.Zhao@mail.wvu.edu
Tel: 304-906-1131

J. Wesley Burnett
Assistant Professor, Division of Resource Management
West Virginia University
Morgantown, WV, 26505-6108
Email: Wesley.Burnett@mail.wvu.edu
Tel: 304-293-5639

Donald J. Lacombe
Associate Professor, Division of Resource Management
West Virginia University
Morgantown, WV, 26505-6108
Email: Donald. Lacombe@mail.wvu.edu
Tel: 304-293-8543

Selected Paper Prepared for presentation at the Agricultural & Applied Economics Association's 2014 AAEA Annual Meeting, Minneapolis, MN, July 27-29, 2014

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 evaluate an empirically testable hypothesis of convergence among provinces. Our results suggest that: (1) CO_2 emission intensities are converging across provinces in China; (2) the rate of convergence is higher with the dynamic panel data model than the cross-sectional regression models; and, (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.

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

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

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). Global climate change is an international problem in scope, yet domestic or regional policies can be implemented to mitigate CO_2 emissions. In the last two decades, carbon dioxide emission intensities (defined as carbon dioxide emission divided by gross domestic product) across the provinces in China have been decreasing year-by-year as illustrated in Figure 1. 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. Zhao et al. (2014) findings suggest that technological improvements in energy consumption and transportation as well as an increase in population density have led to the reduction in CO_2 emission intensity in China. Others have found that structural changes in China's economy (including a decline in emissions in the country's secondary sector) have led to the reduction in emission intensities (Gonzalez and Martinez, 2012; Ma et al., 2012; Ma and Oxley, 2012). However, an examination as to whether the differences in China's province-level CO_2 emission intensities have diminished over time, resulting in convergence, has received little attention in the literature.

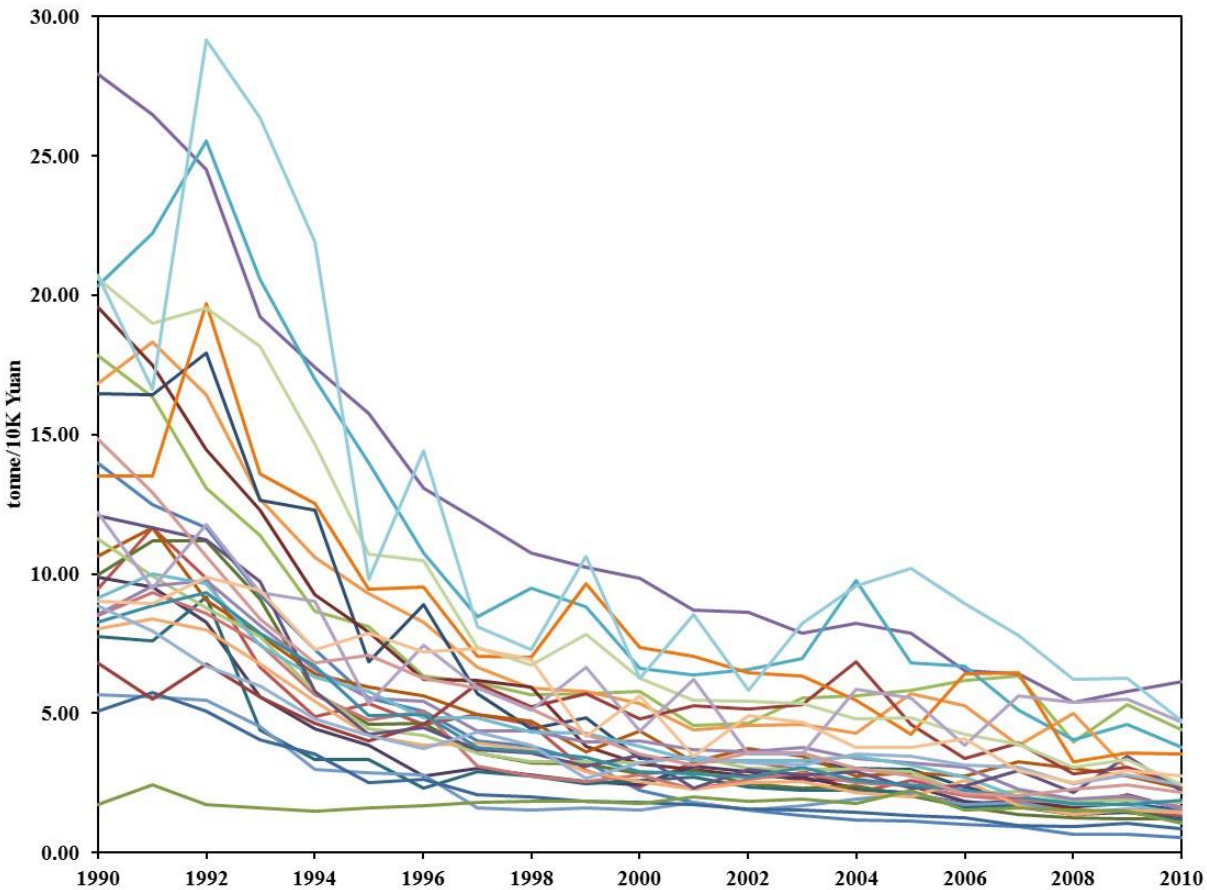

Figure 1. CO_2 emission intensity of each province in China, 1990-2010

In accordance with the Copenhagen Accord, China set the goal to reduce its carbon dioxide emissions per unit of GDP (or carbon intensity) by 40-45% of 2005 levels by 2020. Although CO_2 emission intensities have been declining year-by-year in China as shown in Figure 2, the country still has a long way to go to achieve its reduction goal. If China were to formulate a national climate change policy to ratify such an international agreement then it must begin to look inward to determine the sources and distribution of emission intensity. With this look inward, policy makers may be interested in determining how the distribution of province-level emission intensity is changing over time. Convergence in energy intensity could imply that technological differences across regions diminish over time (Herrerias, 2012). This study seeks to determine interregional differences in technology tend to disappear or increase over time. If differences diminish naturally over time then policymakers may be less worried about a mitigation scheme. If the differences tend to perpetuate or grow over time (which implies a lack of diffusion of energy-related technologies) then it may be too difficult to reach the country's mitigation targets.

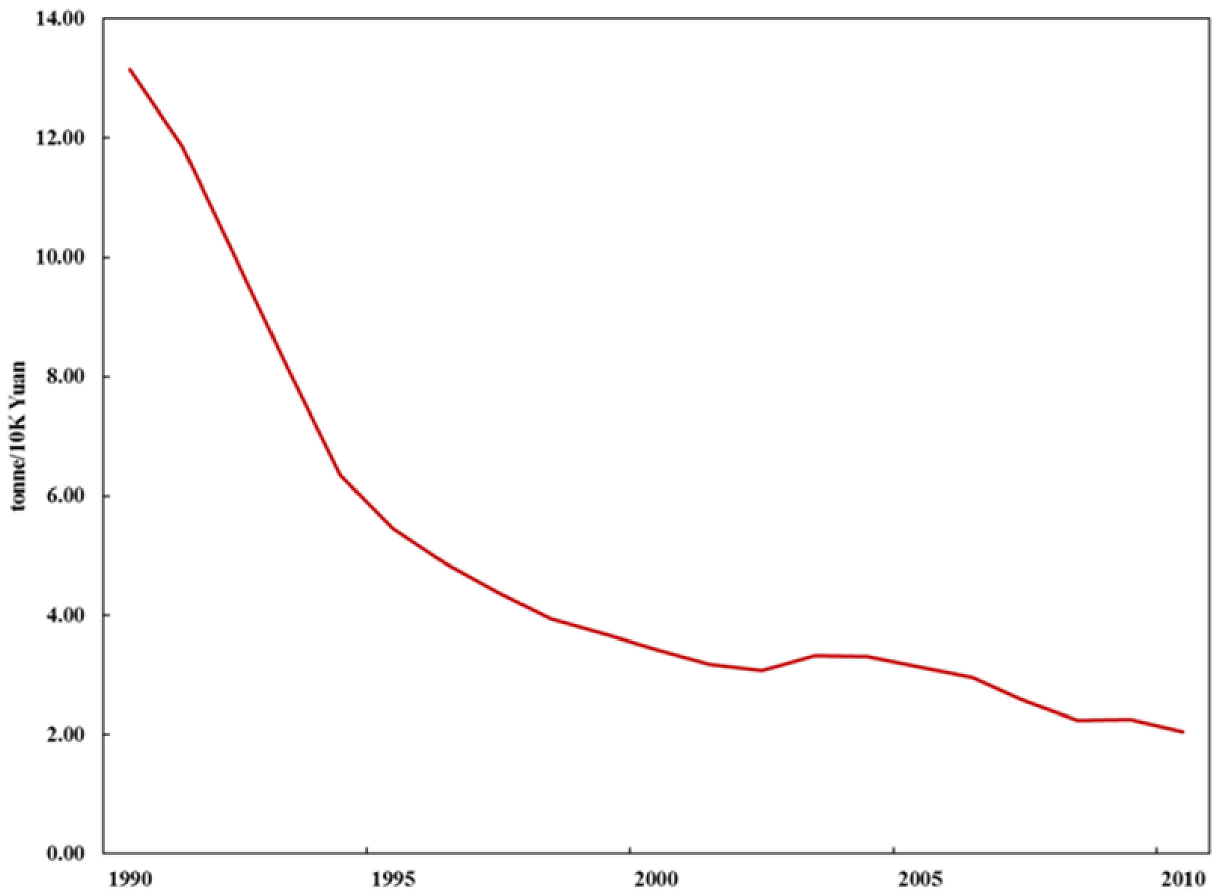

Figure 2. Overall CO_2 emission intensity of China, 1990-2010

The concept of convergence comes from the economic growth literature. In the most general sense, it refers to a decrease in the differences of the economic growth across countries or regions 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, 2007; Duro et al., 2010; Ma and Oxley, 2012; Herrerias, 2012; Herrerias and Liu, 2013). According to Islam (2003), there are different definitions of convergence based on the econometric approach used to measure convergence. Among them, we can distinguish between absolute convergence and conditional convergence, which are often estimated by cross-sectional or panel data techniques. Absolute convergence is defined such that if two or more economies are identical in terms of preferences and technology, then over time they tend to reach the same steady-state growth level (Solow, 1956). Conditional convergence is defined as a type of convergence such that differences in steady-state levels across countries have been controlled for (Islam, 1995). The traditional cross-sectional regression modeling approach implicitly assumes that all regions or economies under consideration have the same steady-state income growth path. Islam (1995) proposed a panel data approach to study growth convergence. The motivation for the panel data approach is to capture the differences across regions or countries. The unobserved differences such as preferences and technology are not easily measurable, so they can be treated as unobserved individual effects in a panel data regression framework (Hsiao, 2002).

There has been tremendous growth in the exploration of spatial issues in the regional economic literatures over the past two or three decades (Anselin, 1998; Gezici and Hewings, 2007). Spatial econometrics is an applied field of econometrics that deals with sample data that is collected with reference to locations measured as points in space. What distinguishes spatial econometrics from traditional econometrics is that the locational data may be characterized by spatial dependence (autocorrelation) or spatial heterogeneity (LeSage and Pace, 2009). In neoclassical growth theory, economies are assumed to be independent; however, technological advances, labor and capital, and environmental policies in one economy might be transmitted to other economies. Ignoring spatial autocorrelation may lead to unreliable statistical inference if spatial dependence is present but omitted in the regression analysis of convergence. Recent advances in spatial econometrics have led to models that control for spatial autocorrelation both in cross-sectional and panel data settings. Spatial autocorrelation can be an important factor in determining regional convergence. To wit, 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 between regions. The preponderance of empirical evidence on regional β-convergence is based almost exclusively on cross-sectional or panel data models without spatial effects. Arguably, 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 estimates of the rate of convergence (Anselin, 1998). Even though the neoclassical economic 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. Thus, incorporating spatial effects into a dynamic panel data model may lead to more efficient estimates of the rate of convergence across provinces.

Hence, the specific aim of this paper is to investigate the convergence of emission intensities among a panel of provinces in China over the period 1990-2010. We follow the work of Yu and Lee (2012) by adopting a spatial, dynamic panel data (SDPD) approach to analyze convergence. After controlling for spatial effects, we investigate how the estimated rate of convergence changes. Compared to previous studies, this study offers two unique contributions to the literature. First, we offer an analysis of the convergence of energy-related emission intensities at the province-level in China. 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 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. Second, we use a novel spatial, dynamic panel data model which includes both the individual effects and the spatial effects. By including the individual effects, we potentially avoid the omitted variable bias in the cross-sectional regression, and by including the spatial effects, we potentially avoid the omitted variable bias in the non-spatial, dynamic panel data regression.

Based on the estimation results, we find evidence that CO_2 emission intensities are converging across provinces in China. We also find that the rate of convergence is higher with the dynamic panel data model (conditional convergence) than with a cross-sectional regression model (absolute convergence). This result is consistent with the study of Islam (1995). The individual effects that are ignored in cross-sectional regressions potentially create omitted variable bias. The panel data framework arguably offers a more precise (efficient) rate of convergence. Finally, we find that 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. This result is consistent with the study of Yu and Lee (2012). According to past literature a significant factor in understanding economic growth convergence is through the persistent difference in levels of technology across regions (Krugman, 1987; Islam, 1995; Jones, 1997). Lesser differences in technology levels suggest that convergence would proceed at a faster rate. Our results imply that technological spillovers, embodied in both the unobserved individual effects and the spatial autocorrelation coefficient, have a direct effect on the rate of convergence of carbon intensity among provinces.

The rest of this paper is structured as follows. Section two introduces the data and methodology. Section three discusses the estimation results. Finally, section four offers conclusions and suggestions for future research.

2 DATA AND METHODOLOGY

2.1 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 annual data on energy consumption and gross domestic products for all the provinces and municipalities (CESY, 1991-2011; CSY, 1991-2011). However, the data set lacks any information on the province-level CO_2 emissions.

In this paper, we estimate the CO_2 emissions for each province by following the revised 1996 Intergovernmental Panel on Climate Change's "Guidelines for National Greenhouse Gas Inventories" (IPCC, 1996). The Carbon Dioxide Information Analysis Center, within the U.S. Department of Energy (DOE), defines carbon dioxide emissions as a linear function of fossil fuel combustion and cement manufacturing (Boden, Marland, and Andres, 2013). More specifically, emissions are estimated by multiplying the amount of fuel usage by a thermal conversion factor as determined by the chemical properties of the fuel. Itkonen (2012) offers a simple explanation of how the energy emissions are estimated

(1) $$CO_{2,t} \equiv \alpha_{oil} \cdot E_t^{oil} + \alpha_{coal} \cdot E_t^{coal} + \alpha_{gas} \cdot E_t^{gas} + \alpha_{flare} \cdot E_t^{flare} + S_t,$$

where $\alpha_{oil}, \alpha_{coal}, \alpha_{gas}, \alpha_{flare} > 0$ are the related thermal conversion factors. Different organizations, such as the DOE, the institute of Energy Economics of Japan, and the Energy Research Institute of National Development and Reform Commission of China, calculate emissions differently, but the differences are often negligible. In this study, we choose coefficients reported by the Energy Research Institute of National Development and Reform Commission (NDRC) of China in 2003.

Following the equation offered by Itkonen (2012), we calculate CO_2 emissions based on the final energy consumption of three primary types of energy sources in China: coal, petroleum and natural gas. We assume that all carbon in the fuel is completely combusted and transformed into carbon dioxide.

2.2 Regression Model

2.2.1 Cross-Sectional Regressions Model

The traditional neoclassical cross-sectional regression model assumes that all regions or economies under consideration have the same steady state income path. In our particular case, this would imply that if provinces have similar technology and environmental policy, then higher emission intensity provinces' emission should decrease faster than lower emission intensity provinces. The general cross-sectional regression model is given as follows

$$\ln(y_{i,t+\tau}) = \alpha + \beta \ln(y_{i,t}) + \varepsilon_{i,t+\tau}, \quad (2)$$

where $y_{i,t}$ is the emission intensity for province i at initial time point t, $y_{i,t+\tau}$ is the emission intensity for province i at the end of time point, $t+\tau$, and τ is the time interval. That is, the regression estimates the rate of convergence of emission intensities over the time period $[t,\ t+\tau]$. We assume that the rate of convergence, β, is defined by an exponential decay function as follows

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

If the regression yields an estimated coefficient, $\hat{\beta}$, that is within the interval $0 < \beta < 1$, then convergence to the steady state is direct and involves no oscillations. The parameter γ is the implied rate of convergence, which can be calculated from the regression results as follows

(4) $$\gamma = -\ln(\hat{\beta}) / \tau .$$

The term "cross-sectional regression" is often confused because there is a province-level index, *i*, and a time interval index, τ, that are specified in (2). Such a specification makes it appear as if this is a panel data approach. However, the subscripts are for notational purposes only. A time interval is specified because the model uses the natural log of province-level emission intensity in the last year of the interval against the natural log of province-level emission intensity in the initial year of the interval. As the interval increases, the effect of the initial condition on the average growth rate declines (Barro and Sala-i-Martin, 2004). Within a large longitudinal or panel data set, one could in principal look at several different intervals across the full sample. Such procedures are often used to omit any trending or cyclical behavior within the data that may affect the convergence estimates. An example is provided by Barro and Sala-i-Martin (2004), in which the authors examine the convergence of personal income across U.S. states for the period 1980-2000. The authors then estimate beta convergence across eleven ten-year-intervals over the entire sample. There is no concrete method for choosing the length of each interval – the selection, although arbitrary, depends on the full sample size and the frequency of observations (i.e., daily, monthly, quarterly, or annually).

As we mentioned above, it is important to investigate the spatial patterns that may indicate the spillover effects among regions. If we include the spatial lag of the dependent variable in the equation, then we derive the cross-sectional spatial autoregressive (SAR) model (Rey and Montouri, 1999) as follows

(5) $$\ln(y_{i,t+\tau}) = \alpha + \rho \sum_{j=1}^{N} W_{ij} \ln(y_{i,t+\tau}) + \beta \ln(y_{i,t}) + \varepsilon_{i,t+\tau},$$

where ρ denotes the scalar, spatial autoregressive parameter on the dependent variable, W_{ij} is the *i, j-th* element of a pre-specified nonnegative ($N \times N$) spatial weighting matrix *W*. In this study, we choose a binary contiguity matrix, which is determined by observing whether 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 are $W_{ij} = 1$, and $W_{ij} = 0$ otherwise. Consistent with the literature, we normalize the spatial weight matrix by performing row-standardization (LeSage and Pace, 2009). That is, the sum of elements W_{ij} in each row equals one. This transformation of the spatial weight matrix provides for an intuitive explanation so that any variable pre-multiplied by the spatial weight matrix will represent a weighted average of the surrounding observations.

Furthermore, if we include both the contemporary spatial effects and the lagged spatial effects in the equation (Yu and Lee, 2012), then we would derive the spatial cross-sectional regression model

(6) $$\ln(y_{i,t+\tau}) = \alpha + \rho \sum_{j=1}^{N} W_{ij} \ln(y_{i,t+\tau}) + \beta \ln(y_{i,t}) + \lambda \sum_{j=1}^{N} W_{ij} \ln(y_{i,t}) + \varepsilon_{i,t+\tau},$$

where λ is spatial autocorrelation coefficient on the initial emission intensity levels.

Overall, since there are no controls on province-level heterogeneous fixed effects in the above cross-sectional regression and spatial regression models, the estimates are interpreted as absolute convergence.

2.2.2 Dynamic Panel Data Model

As Quah (1993) points out, the traditional cross-sectional approach does not reveal the dynamics of the growth processes. In response, Islam (1995) proposed a panel data approach to study growth convergence. The motivation for the panel data approach is to capture the differences across regions or countries. The unobserved differences such as preferences and technology are not easily measurable, so they can be treated as unobserved individual effects in a panel data regression context (Hsiao, 2002). The general econometric specification of a dynamic panel data model is given as follows

(7) $$\ln(y_{i,t}) = \beta \ln(y_{i,t-1}) + \mu_i + \varepsilon_{i,t},$$

where μ_i denotes the individual effect for each province. To avoid confusion between the cross-sectional models in the previous subsection, we use the subscript i to denote each region and t to denote each time period. Note the contrast between τ in the previous subsection and t in the current subsection. With the approach in this subsection, we examine beta convergence within a longitudinal or pooled data set. It should be noted that in principle one could examine the panel data within intervals as well.

Even though the dynamic panel data model could reveal the dynamic growth process, there are may be spillover effects from one region to the adjacent regions. For example, technological diffusion and environmental policies may follow a spatial pattern as regions may have different capacities to create or absorb new technologies and policies. Therefore, our modeling approach seeks to control for spatial autocorrelation within a dynamic panel data framework.

Similar to the cross-sectional model, if we include the spatial lag of the dependent variable in the equation, then we derive the dynamic panel SAR model as follows

(8) $$\ln(y_{i,t}) = \rho \sum_{j=1}^{N} W_{ij} \ln(y_{i,t}) + \beta \ln(y_{i,t-1}) + \mu_i + \varepsilon_{it}$$.

Further, if we include both the contemporary spatial effects and the lagged spatial effects in the equation, then we derive the spatial dynamic panel data model as follows

(9) $$\ln(y_{i,t}) = \rho \sum_{j=1}^{N} W_{ij} \ln(y_{i,t}) + \beta \ln(y_{i,t-1}) + \lambda \sum_{j=1}^{N} W_{ij} \ln(y_{i,t-1}) + \mu_i + \varepsilon_{it}$$.

While the cross-sectional estimates might be better interpreted as rates of absolute convergence, those of the panel models can be interpreted as the rates of conditional convergence. Conditional convergence is interpreted as convergence after differences in the steady states across different regions have been controlled for; i.e., by controlling for the heterogeneous fixed effects, μ_i.

3 ESTIMATION RESULTS

In this study, we divide the entire sample into several shorter time intervals. As Islam (1995) argued, one can use a time span for just one year, which is technically feasible given that the underlying data set is offered annually. However, yearly time spans are generally too short to be appropriate for studying growth convergence. In other words, short-term disturbances may loom large in such brief time spans. Additionally, by considering the spatial effects, a shorter time span, such as one or two year span may be inappropriate because the spillover effects (such as technological spillovers) might take several years to propagate across regions. Hence, we choose five-year time intervals as is done in Islam's (1995) use of the dynamic panel data approach and in accordance with China's "Five-Year Plans"; i.e., $\tau = 5$. Therefore, we use the corresponding years for our analysis: 1990, 1995, 2000, 2005, and 2010. Following Yu and Lee (2012), we also estimate the model with four-year intervals to check whether the results are robust to different time interval specifications.

3.1 Empirical Results Using Cross Sections

In this section, we estimate the single cross-sectional regression model for the entire sample period, and estimate pooled cross-sectional regression models with five-year and four-year intervals. For the single cross-sectional regression model, we regress $\ln(y_{2010})$ on $\ln(y_{1990})$. For the five-year spans, we regress $\ln(y_{2010})$ on $\ln(y_{2005})$, $\ln(y_{2005})$ on $\ln(y_{2000})$, $\ln(y_{2000})$ on $\ln(y_{1995})$, and $\ln(y_{1995})$ on $\ln(y_{1990})$. Consistent with Yu and Lee (2012), we then construct the mean value of convergence based on all of the regressions. We also present the parameter estimates for the four-year interval specification. The results of the cross-sectional regression without spatial effects is presented in Table 1.

Table 1. Cross-Sectional Regression without Spatial Effects

	Period	Constant	β	R^2	Implied γ ($\beta = e^{-\tau\gamma}$)
Single Cross Sectional Regression	1990-2010	-0.6556 (-1.6762)	0.5574*** (3.4738)	0.3012	0.0292 (τ=20)
Pooled Regression with 5 Year Intervals	1990-1995	-0.2594 (-1.4281)	0.8350*** (11.2043)	0.8176	
	1995-2000	-0.0663 (-0.4208)	0.7837*** (8.9314)	0.7402	
	2000-2005	-0.0911 (-0.6071)	0.9617*** (8.7389)	0.7317	
	2005-2010	-0.4482 (-4.2141)	0.9753*** (11.4824)	0.8248	
	Joint subperiods	-0.2162 (-1.6675)	0.8889*** (10.0893)	0.7786	0.0236 (τ=5)
Pooled Regression with 4 Year Intervals	1990-1994	-0.3773* (-1.8758)	0.9659*** (11.7057)	0.8243	
	1994-1998	0.1381 (0.9151)	0.6886*** (9.1389)	0.7400	
	1998-2002	-0.0475 (-0.3883)	0.8615*** (10.7684)	0.7986	
	2002-2006	-0.3486** (-2.7464)	1.1367*** (11.5074)	0.8192	
	2006-2010	-0.2644*** (-2.8595)	0.9096*** (11.4108)	0.8167	
	Joint subperiods	-0.1800 (-1.3910)	0.9125*** (10.9063)	0.7998	0.0229 (τ=4)

From the table, we find that the coefficients of the initial emission intensity are positive and significant for both the single cross-sectional regression and the pooled regressions, and the values are all between zero and one. These results imply that CO_2 emission intensities are converging across provinces in China. For the entire sample period specification, the implied rate of convergence is 0.0292 for the single cross-sectional regression. The five-year and four-year interval specifications yield estimated rates of convergence of 0.0236 and 0.0229, respectively. Therefore, the pooled cross-sectional regression yield similar results to the single cross-sectional results.

Table 2 reports the estimation of the cross-sectional SAR model. As revealed in the table, the single cross-sectional regression yields a rate of convergence of 0.0345 for the entire sample period. And by using five-year and four-year intervals, the estimated rates of convergence are 0.0167 and 0.0217, respectively. Therefore, these regressions yield similar rates of convergence as the non-spatial models.

Table 2. Cross-Sectional Regression with Contemporary Spatial Effects

	Period	Constant	β	ρ	R^2	Implied γ ($\beta = e^{-\tau\gamma}$)
Single Cross Sectional Regression	1990-2010	-0.6237* (-1.6595)	0.5001*** (2.8826)	0.1470 (0.6299)	0.2915	0.0345 (τ=20)
Pooled Regression with 5 Year Intervals	1990-1995	-0.2596 (-1.4658)	0.8386*** (6.9081)	-0.0047 (-0.0322)	0.8111	
	1995-2000	-0.0222 (-0.1392)	0.8469*** (7.0515)	-0.1179 (-0.7597)	0.7476	
	2000-2005	-0.0212 (-0.1241)	1.0279*** (8.3092)	-0.1339 (-0.8666)	0.7205	
	2005-2010	-0.4598*** (-4.0914)	0.9656*** (10.5532)	0.0320 (0.8111)	0.8188	
	Joint subperiods	-0.1907 (-1.4551)	0.9198*** (8.2055)	-0.0561 (0.2119)	0.7745	0.0167 (τ=5)
Pooled Regression with 4 Year Intervals	1990-1994	-0.3787* (-1.9481)	0.9048*** (6.6889)	0.0759 (0.5227)	0.8229	
	1994-1998	0.1002 (0.6269)	0.6229*** (5.9696)	0.1119 (0.7647)	0.7432	
	1998-2002	0.0733 (0.5988)	1.0024*** (9.8712)	-0.2659** (-2.0530)	0.8265	
	2002-2006	-0.3557** (-2.5253)	1.1304*** (10.1898)	0.0140 (0.1074)	0.8197	
	2006-2010	-0.2467** (-2.2923)	0.9234*** (10.6697)	-0.0450 (-0.3154)	0.8163	
	Joint subperiods	-0.1615 (-1.1080)	0.9168*** (8.6778)	-0.0204 (-0.1947)	0.8057	0.0217 (τ=4)

Table 3 presents the results which include both contemporary spatial effects and lagged spatial effects. The estimated rates of convergence in this single cross-sectional regression is 0.0380, and the estimated rates of convergence are 0.0185 and 0.0239 for the pooled cross-sectional regressions with five and four year intervals. These regressions also yield similar rates of convergence with the non-spatial model and cross-sectional SAR model.

Table 3. Cross-Sectional Regression with Contemporary Spatial Effects and Lagged Spatial Effects

	Period	Constant	β	ρ	λ	R^2	Implied γ ($\beta = e^{-\tau\gamma}$)
Single Cross Sectional Regression	1990-2010	-0.6219* (-1.6581)	0.4673** (2.4667)	0.1380 (0.5910)	0.0350 (0.5187)	0.2985	0.0380 (τ=20)
Pooled Regression with 5 Year Intervals	1990-1995	-0.2569 (-1.4737)	0.8159*** (6.5032)	-0.0139 (-0.0954)	0.0286 (0.9117)	0.8093	
	1995-2000	-0.0226 (-0.1411)	0.8471*** (6.7522)	-0.1149 (-0.7356)	-0.0018 (-0.0384)	0.7379	
	2000-2005	-0.0213 (-0.1242)	1.0299*** (8.0261)	-0.1319 (-0.8272)	-0.0042 (-0.0583)	0.7103	
	2005-2010	-0.4755*** (-4.1993)	0.9531*** (10.2716)	-0.0129 (-0.0940)	0.0553 (0.8599)	0.8166	
	Joint subperiods	-0.1941 (-1.4846)	0.9115*** (7.8883)	-0.0684 (-0.4447)	0.0195 (0.4381)	0.7685	0.0185 (τ=5)
Pooled Regression with 4 Year Intervals	1990-1994	-0.3789* (-1.9480)	0.9111*** (6.6279)	0.0719 (0.4929)	-0.0030 (-0.0841)	0.8165	
	1994-1998	0.0968 (0.6118)	0.6092*** (5.6640)	0.1019 (0.6916)	0.0233 (0.5844)	0.7365	
	1998-2002	0.0757 (0.6279)	0.9854*** (9.4548)	-0.2849** (-2.2059)	0.0318 (0.7511)	0.8247	
	2002-2006	-0.3572** (-2.5345)	1.1245*** (9.7909)	0.0049 (0.0371)	0.0152 (0.2256)	0.8131	
	2006-2010	-0.2532** (-2.3333)	0.9145*** (10.1748)	-0.0710 (-0.4804)	0.0336 (0.4632)	0.8100	
	Joint subperiods	-0.1634 (-1.1152)	0.9089*** (8.3424)	-0.0354 (-0.2929)	0.0202 (0.3880)	0.8000	0.0239 (τ=4)

However, the spatial effects in Table 2 and Table 3 are not significant. This might be due to omitted individual or heterogeneous effects. In a cross-sectional regression framework, it is difficulty to account for unobservable or unmeasurable factors such as preferences and technology. Omission of such factors may lead to biased estimated rates of convergence. In the following section we extend the analysis to include the individual effects within a spatial, dynamic panel data model and compare the previous results with the estimated rates of convergence from the spatial dynamic panel data model.

3.2 Empirical Results Using Dynamic Panel Data

According to Barro and Sala-i-Martin (2004), one advantage of panel data over cross sections is that one does not need to hold constant the steady state growth level because it is implicitly estimated using fixed effects. One potential problem with panel data models is that one needs a sufficiently large amount of time series observations in order to overcome dynamic panel data bias (Nickell, 1981; Judson and Owen, 1999). Dynamic panel data bias occurs when a lagged dependent variable is specified on the right hand side of the regression and the panel does not contain enough time series observations. To help ensure that we are getting efficient estimates of the speed of convergence, we use the bias-corrected least squares dummy variable (LSDVC) model. Judson and Owen (1999) showed that the LSDVC model provided the least biased estimates of the coefficient on the lagged dependent variable. The results presented in this section are the bias-corrected results.

The results of the dynamic panel data model without spatial effects are presented in Table 4. Here, we see that the estimated rate of convergence is 0.1787 for the five year spans, and is 0.1403 for the four year spans. They are larger than the cross-sectional estimates of 0.0236 and 0.0229 in Table 1. Hence, after controlling for the unobserved individual effects, we have a higher rate of convergence.

Table 4. Dynamic Panel without Spatial Effects

	β	R^2	Implied γ ($\beta = e^{-\tau\gamma}$)
5 Year Intervals	0.4092**	0.8552	0.1787
	(17.1500)		(τ=5)
4 Year Intervals	0.5706**	0.8971	0.1403
	(16.4400)		(τ=4)

Table 5. Dynamic Panel with Contemporary Spatial Effects

	β	ρ	R^2	Implied γ ($\beta = e^{-\tau\gamma}$)
5 Year Intervals	0.3959***	0.4570***	0.9037	0.1853
	(5.9401)	(5.3752)		(τ=5)
4 Year Intervals	0.5081***	0.3799***	0.9155	0.1693
	(8.1268)	(5.0551)		(τ=4)

The results for the dynamic panel SAR model and the SDPD model are summarized in Table 5 and Table 6, respectively. We find that the spatial effects are positive and statistically significant in Table 5 and Table 6. This implies that province-level CO_2 emission intensities are spatially correlated in China and suggest that we should consider the spatial correlation in the growth regressions; otherwise there might be omitted variable bias due to excluding the spatial effects.

Table 6. Dynamic Panel with Contemporary Spatial Effects and Lagged Spatial Effects

	β	ρ	λ	R^2	Implied γ ($\beta = e^{-\tau\gamma}$)
5 Year Intervals	0.3847***	0.4450***	0.0217	0.9035	0.1911
	(3.6918)	(4.4751)	(0.1688)		(τ=5)
4 Year Intervals	0.4416***	0.3010***	0.1423	0.9153	0.2043
	(5.1105)	(3.0026)	(1.2042)		(τ=4)

Strangely, the results for the dynamic spatial panel data model provided statistically insignificant estimates on the parameter of the temporally and spatially lagged autocorrelation coefficient, λ, in Tables 3 and 6. Since we used four- and five-year interval specifications (which may cause this lack of significance because we are filtering out economic cycles), we tested the model by using the full data set (i.e., we used one year time intervals), but we found similar results that λ is still insignificant (results not provided), which implies the insignificance is not due to the interval specification. A possible explanation for the lack of statistical significance of λ is that each province implements short-run strategies to reduce emission intensity to comply with pressures from the national government. This is further reinforced by the significance of ρ, which is the parameter on the contemporaneous spatially lagged dependent variable. These parameters suggest perhaps that provinces are adopting short-run measures to ease emission intensity, which explains the evidence of spatial dependence found with the significance of contemporaneous spatially lagged variable. The lack of significance of λ may suggest that individual provinces are adopting different medium-run strategies or policies to reduce emission intensity. If the medium run strategies are not uniform across provinces then we would not expect to see evidence of spatial spillovers in the temporally and spatially lagged dependent variable. This may also imply that provinces are endogenously enforcing rules to improve the environmental quality, which is found by Wang and Wheeler (1999). In our case, this suggests that medium-run, province-level policies to reduce carbon emission intensities are not uniform.

For the dynamic panel SAR model, the rate of convergence of the five-year and four-year spans are 0.1853 and 0.1693, respectively, which are larger than the cross-sectional estimates of 0.0167 and 0.0217 in Table 2. For the SDPD model, the rate of convergence of the five year and four year spans are 0.1911 and 0.2043, respectively, which are also larger than the cross-sectional estimates of 0.0185 and 0.0239 in Table 3. Therefore, estimated rate of convergence is higher with the dynamic panel data than the cross-sectional regression. We can also interpret this as the rate of conditional convergence is higher than the absolute convergence.

After considering the spatial effects, the rate of convergence of the dynamic panel SAR model and the SDPD model with five-year intervals are 0.1853 and 0.1911, which are larger than the rate of convergence of the non-spatial panel data model. We similar results with the four-year intervals as well. Therefore, it appears that technological spillovers are reducing the persistent technological differences among the provinces, and thus leading to a faster rate of convergence.

4 CONCLUSIONS

In this paper, we analyzed the provincial convergence of CO_2 emission intensity in China. We proposed a spatial dynamic panel data approach that controls for both time and space – this differs from the conventional panel date convergence literature which does not control for spatial autocorrelation. By using a spatial dynamic panel data model we potentially avoid omitted variable bias if the underlying data are characterized by spatial dependence.

The findings of the province-level convergence of CO_2 emission intensity imply that the provinces with high emission intensity and provinces with low emission intensity are tending to convergence to the same steady state equilibrium over time. In other words, the province-level disparity of CO_2 emission intensity is gradually shrinking over time, which implies that the differences in technology are becoming less persistent across provinces.

By controlling for the heterogeneous effects and spatial effects, we are potentially controlling for tangible and intangible factors such as energy consumption, technology, and the province's energy infrastructure. Improvements in these factors may have direct positive effects on the provinces' short-run emission intensity level. After controlling for individual and spatial effects, the higher estimated rate of convergence suggests that technological spillovers have an effect on the rate of convergence of carbon intensities in China.

The statistically significant spatial autocorrelation suggests that, while provinces may be converging to a unique steady state equilibrium, they do not do so independently but rather tend to display movements similar to their regional neighbors. The results from the spatial, dynamic panel data model suggest that own-province policies may have an effect on neighboring provinces and vice versa in the short run, but not necessarily in the medium/long run. The lack of statistical significance of spatial effects in the long run suggests that provinces are not adopting uniform policies to mitigate carbon dioxide emissions intensities.

A potential limitation within this study is due to the relative short nature along the time dimension of our data set. The natural process of convergence can take several decades if not longer to play out. Unfortunately, our data is limited to that which is provided by the Chinese government. Given China's rapid economic advancements, our results are perhaps telling of an initial sign of convergence, which suggests that provinces may have an easier task of negotiating coordinated emission reduction targets in the future. As additional data comes available it will be important for future studies to examine this relationship further in China.

REFERENCES

Aldy, J.E., 2006. Per capita carbon dioxide emissions: Convergence or divergence? Environmental & Resource Economics 33, 533-555.

Anselin, L., 1998. Spatial Econometrics: Methods and Models. Kluwer Academic Publishers, Dordrecht.

Boden, T.A., G. Marland, and R.J. Andres. 2013. Global, Regional, and National Fossil-Fuel CO2 Emissions. Carbon Dioxided Information Analysis Center, Oak Ridge National Laboratory, U.S. Department of Energy, Oak Ridge, Tenn. U.S.A. doi 10.3334/CDIAC/00001_V2013.

Barro, R.J., Sala-i-Martin, 2004. Economic Growth: MIT Press.

CESY, 1991-2011. China Energy Statistical Yearbook. In: Commission, N.D.A.R. (Ed.). National Bureau of Statistics of China.

Conley, T.G., Ligon, E., 2002. Economic distance and cross-country spillovers. J Econ Growth 7, 157-187.

CSY, 1991-2011. China Statistical Yearbook. National Bureau of Statistics of China.

Duro, J.A., Alcantara, V., Padilla, E., 2010. International inequality in energy intensity levels and the role of production composition and energy efficiency: An analysis of OECD countries. Ecological Economics 69, 2468-2474.

Ezcurra, R., 2007. Distribution dynamics of energy intensities: A cross-country analysis. Energy Policy 35, 5254-5259.

Gezici, F., Hewings, G.J.D., 2007. Spatial analysis of regional inequalities in Turkey. European Planning Studies 15, 383-403.

Gonzalez, D., Martinez, M., 2012. Changes in CO2 emission intensities in the Mexican industry. Energy Policy 51, 149-163.

Herrerias, M.J., 2012. World energy intensity convergence revisited: A weighted distribution dynamic approach. Energy Policy 49, 383-399.

Herrerias, M.J., Liu, G., 2013. Electricity intensity across Chinese provinces: New evidence on convergence and threshold effects. Energy Economics 36, 268-276.

Hsiao, C., 2002. Analysis of Panel Data: Cambridge University Press.

Jones, C., 1997. On the evolution of the world income distribution. Journal of Economic Perspectives 11, 19-36.

Judson, R.A., Owen, A.L., 1999. Estimating dynamic panel data models: a guide for macroeconomists. Economic Letters 65, 9-15.

Krugman, P., 1987. The narrow moving band, the Dutch disease, and the competitive consequences of Mrs Thatcher. Journal of Development Economics 45, 1-28.

LeSage, J.P., Pace, P.K., 2009. Introduction to Spatial Econometric. CRC Press, Boca Raton.

Itkonen, J.V.A., 2012. Problems estimating the carbon Kuznets curve. Energy 39, 274-280.

Intergovernmental Panel on Climate Change, 1996. "Revised 1996 IPCC guidelines for national greenhouse gas inventories: Workbook volume 2." Technical report, United Nations.

Islam, N., 1995. Growth Empirics: A Panel Data Approach. The Quarterly Journal of Economics 110, 1127-1170.

Islam, N., 2003. What have we learnt from the convergence debate? Journal of Economic Surverys 17, 309-362.

Liddle, B., 2010. Revisiting world energy intensity convergence for regional differences. Applied Energy 87, 3218-3225.

Ma, D.C., Hu, S.Y., Zhu, B., Jin, Y., 2012. Carbon substance flow analysis and CO2 emission scenario analysis for China. Clean Technologies and Environmental Policy 14, 815-825.

Ma, H., Oxley, L., 2012. The emergence and evolution of regional convergence clusters in China's energy markets. Energy Economics 34, 82-94.

Nickell, S., 1981. Biases in Dynamic-Models with Fixed Effects. Econometrics 49, 1417-1426.

Quah, D., 1993. Galtons Fallacy and Tests of the Convergence Hypothesis. Scandinavian Journal of Economics 95, 427-443.

Rey, S.J., Montouri, B.D., 1999. US regional income convergence: A spatial econometric perspective. Regional Studies 33, 143-156.

Solow, R.M., 1956. A Contribution to the Theory of Economic Growth. Quarterly Journal of Economics 70, 65-94.

Wang, H., Wheeler, D., 1999. Endogenous Enforcement and Effectiveness of China’s Pollution Levy System. Development Research Group. World Bank.

Yu, J.H., Lee, L.F., 2012. Convergence: A spatial dynamic panel data approach. Global Journal of Economics 1, 36.

Zhao, X., Burnett, J.W., Fletcher, J.J., 2014. Spatial Analysis of China Province-Level CO2 Emission Intensity. Renewable and Sustainable Energy Reviews 33, 1-10.