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Summary

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Keywords: Mitigation, Economic growth, Spatial Interaction, Spatial Durbin Model

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Abstract: China is faced with the big challenge of maintaining a remarkable economic growth in an environmental friendly manner; that is why forecasting the turning point is of necessity. Traditional econometric approaches do not consider the spatial dependence that inevitably exists in the economic units, which probably risks misspecification and generating a biased estimation result. This paper firstly constructs Theil index to measure the intra-and inter regional inequality of CO_2 emissions, we find that difference in emissions between regions is narrowed but gap within the Western China is sharply expanding. Then the Spatial Durbin model is employed to shape the relationship between mitigation and economic growth using the panel data of 29 provinces ranging from 1995 to 2011. Results show that the peak of per capita carbon dioxide emissions in China would be seen when GDP per capita reaches between $USD 21594 to 24737 (at 2000 constant price), much smaller when compared with the estimations of models which ignore the spatial dependence. This implies that territorial policy and industry transfer, on one hand would favor those underdeveloped regions with investment, technology and labors transfer; on the other hand enables developed regions more potential to mitigation, thus, chances are that China achieves the emissions peak of carbon dioxide earlier than conventional wisdom.

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1. Introduction

Climate change is one of the most critical and most daunting challenges facing policy makers in the 21 century on a global scale (Aldy et al., 2009). As the biggest CO_2 emitter and energy consumer, China is pressed to mitigation from rounds of international deliberations. Obviously, Figure 1 shows that China has achieved an 8.6% and 6.5% increase in CO_2 emissions at national level and individual level during the past six decades, in other words, a turning point of emissions at neither level has occurred yet. It seems harder for a developing country to hold CO_2 emissions in check while maintain a sustainable economic growth (Wei, 2014). However, as China's large contribution to the global emissions would have great impact on the achievement of a world 2-Celcius threshold, he has taken actions to participate in the international mitigation club, though China has been free from any binding targets under the Kyoto Protocol. For example, the State Council in 2006 set the target of reducing China's energy intensity by 20% during the Eleventh Five−Year Plan. Also in Copenhagen Conference, China was committed to reducing the 40—45% carbon intensity (carbon dioxide emissions per unit of GDP) by 2020 as compared with a 2005 baseline. Besides, most provinces are allocated with a specific mitigation target in order to fulfill the total target. By evaluating the performance of each participant during the Eleventh Five-Year Plan, we found that the Eastern China has done much better than the nationwide average level. Particularly, regions clustering around the Pearl River Delta Economic Zone and the Yangtze River Delta Economic Zone reduced their energy intensity by over 80 percent on time. Beijing and Tianjin even pulled their deadline one year ahead of schedule.

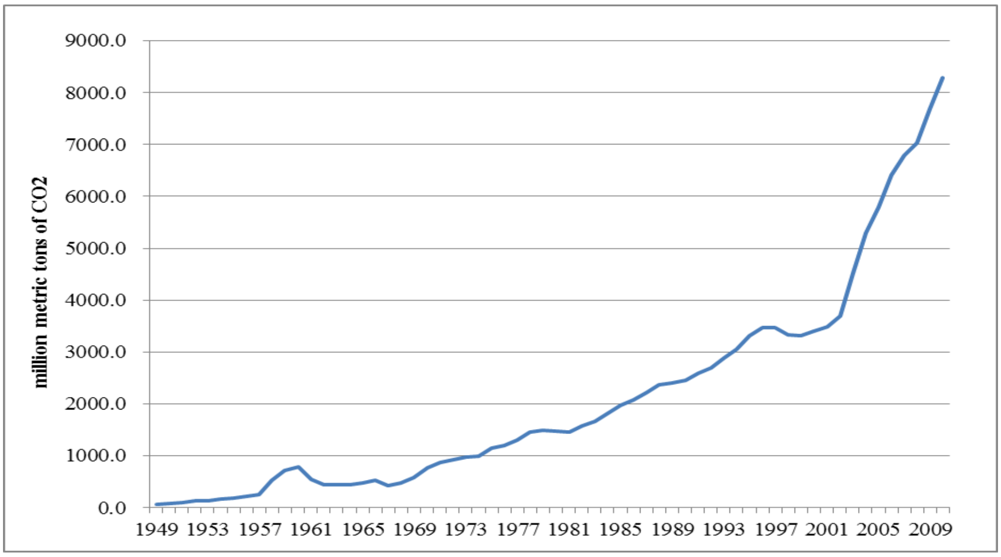

Fig.1. China's total CO_2 emissions from 1949 to 2009

In fact, provinces within each region are taking geographical as well as economic connections, in other words, the government of one particular place might adjust its regulations in response to policy changes in its neighboring regions. Specifically, the East China has a rapid economic growth and relatively advanced social development. Provinces that cluster in the east part are capable to exert a positive influence interactively by means of sharing or mimicking each other's development patterns, which in turn promotes their local development. However, the Middle and West China is in the pace of development accompanied by large investment and energy consumption in infrastructure construction. Therefore, it is possible to say that provinces in the East China might be actively affected by the neighboring area, but provinces in the Middle and West China might have to compete for the resources.

Additionally, spatial effects work interactively between regions (See Figure 2). According to the Twelfth Five-Year Plan, the East China is still functioned as a leading role in driving the national economic growth but at same time has to undertake heavier mitigation targets, while more attention is paid to the northeast, the middle and west parts on revitalization and exploitation. In other words, it is more likely that initially the east region has transferred the industry embedded by investment, labor and technology to facilitate the construction of the western region; nevertheless at the same time unexpectedly exported carbon emissions as well. Years later, the underdeveloped area can in turn benefit from the spillover of the advanced technology for mitigation. Chances are that the underdeveloped regions are attempting to find a sustainable way to improve their development patterns with the help of those industrial provinces.

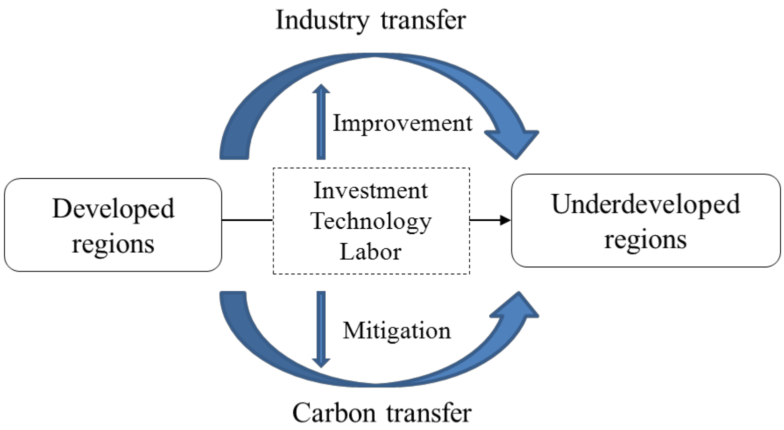

Fig. 2 Spatial interactions between developed and underdeveloped regions

Technically, it is important to figure out the peak emissions before we finally find out the best solution to balance the economic growth and the environmental degradation. A large body of literature used econometric approaches to make a forecast. However, the cross sections are assumed to be geographically independent according to the conventional econometric techniques, in other words, the interactions of economic units in space are not included in the model specification, yet the space can be physical or economic in nature (Lee and Yu, 2009). The geographical proximity, resource endowment, economic behavior, preference and policy relevance all make it necessary to consider the similarities among neighboring places, thus, as pointed out by Maddison (2006), spatial relationships with regard to environment issues arise most obviously as a consequence of countries' strategic response to transboundary pollution flows. The spatial effects, in a way, help to promote the development of each region, for example, by constructing the economic zone, then how will spatial connections affect China's mitigation process? Actually, it appears that researchers recently has started to pay closer attention to the effects on neighboring area when solving energy issues after Maddison (2006) explicitly empirically accounted for the Environmental Kuznets curve using spatial techniques. However, researches upon energy and environment in China have seldom utilized spatial econometric tools to handle with spatial dependency. Under such circumstances, this paper presents an initial step to explore how regional interactions in space affect China's mitigation targets and economic development. Concretely, the panel data of 29 provinces ranging from 1995 to 2011 are utilized to complete the estimation, with an attempt to track China's carbon trajectory before reaching the emissions peak and also to search the mitigation pathway in a more rational manner.

The setup of this article is as follows. Section 2 summarized the methods and main findings of previous CKC research. Section 3 describes the methodology and data sources in this study. Section 4 reports the results that are obtained using methods with and without spatial connections. Conclusions are discussed in Section 5.

2. Literature Review

Research on the relationship between environment and economics shows little sign of diminishing since Grossman and Kruger (1991) first proposed the Environmental Kuznets Curve (EKC). EKC is an empirical hypothesis, asserting that income would worsen the environmental degradation at the beginning of industrialization until reaching a point when the pollution reaches maximum level, and afterwards the environmental quality improves as income increases. Given numerous reviews on generalized EKC, we would not elaborate on the main findings.

Recently, researchers have paid much closer attention to the relationship between carbon emissions and economic growth, mainly on two topics: exploring whether emission is compatible with income or forecasting when and how much for the world or a specific region to reach peak emissions. When it comes to the first topic, much literature suggests different outcomes occur as pollutants or countries vary in studies. Aldy (2005) defines the production-based and consumption-based CO_2 emissions and then uses panel regression model based on the state-level information and clearly notes that states in the US do not follow the same form of curves. Dijkgraaf and Vollebergh (2005) challenge the existence of an overall EKC for carbon emissions (CKC) by analyzing OECD countries from 1960 to 1997. Richmond and Kaufmann (2005) combine panel unit root test and cointegration test of OECD countries as well as non-OECD countries and point out that there is little evidence of CKC for OECD countries and no evidence for non-OECD countries. Fu (2008) uses cointegration test on 44 countries in terms of production-based and consumption-based emissions and notes that either production- or consumption based CKC displays an inverted-U shape. Han and Lu (2009) first classify 165 countries into four groups according to their industrialization and income level and then discuss the emission-and-income relationship of each group. Results show that Countries with high industrialization and high income have an inverted U-shape CKC curve; Countries with low industrialization and low income as well as with low industrialization and high income take an N-shape CKC curve; while emissions of countries with high industrialization and low income increase monotonously with income. In short, the shape of Environmental Kuznets Curve for carbon emissions varies greatly as different countries and pollutants are selected for research.

As to the second topic, much literature forecasts the emissions and income that correspond to the turning point. Schmalensee, Stoker and Judson (1998) estimate peak emissions of 100 countries based on panel data regression and scenario analysis. It is reported that peak emissions in the U.S.A occurred in 1970, the United Kingdom and Japan in 1973, Canada in 1979. In Affhammer and Carson’s research targeted at China (2008), “downturn is highly unlikely until 2010 unless there are substantial changes”. They also forecast that China’s annual growth rate is within 11.05~11.88% from 2000 to 2010. Xu and Song (2010) use cointegration test and scenario analysis to forecast China’s emissions extended to the east, the middle and the west parts. According to their research, China will achieve peak emissions at 2027 at the national level; East and Middle China both have an inverted-U shape curve and peak years of each province are matched; however, not any CKC shape occurs in the West China.

In short, methods for researches on the relationship between carbon emissions and economic growth have extended from time series or cross-sectional estimation to wide use of panel data estimation which is believed to offer more modeling possibilities and increases estimation efficiency due to the inclusion of more variation and less collinearity among variables (Elhorst, 2003). As many researchers point out that parameters are not homogeneous over space but instead geographically vary, it is clear that omitting spatial variation might risk misspecification and generating the spurious estimation of parameters. In other words, panel data with spatial interaction is of great interest, as it enables researchers to take into account the dynamics and control for the unobservable heterogeneity (Anselin, 1988; Baltagi et al., 2003, 2007; Elhorst, 2003; Kapoor et al., 2007; Yu et al., 2007, 2008). Recently, researchers attempt to apply spatial panel models (Anselin, 2009) to quite a few topics like house price, transportation research, agriculture economics and political election, to name a few and compare the results considering cross dependence with those of old methods. In particular, some existing studies discuss China’s energy issues in light of the spatial autocorrelation among provinces. This paper provides the initial step to further explore how provincial interactions affect the relationship between economic growth and carbon emissions in China by using spatial panel models.

3. Methodology

Recently, the spatial econometric literature has exhibited a growing interest in the specification and estimation based on spatial panels (Elhorst, 2012). Unlike the hypothesis of conventional econometrical techniques that data set is geographically independent, spatial panel models take spatial connections into consideration, which is believed not likely to yield an inconsistent and biased estimation of parameters.

Spatial data can be modelled in a variety of ways, among which three widely recognized forms are presented here. One model contains a spatially lagged dependent variable which is called spatial lag model. In this model, the value of the dependent variable observed at one particular location is jointly determined by the average value of the dependent variable of the neighborhoods. The spatial lag model in matrix form can be formulated as

$$Y = \rho WY + \beta X + \alpha + e \tag{1}$$

where Y is a vector of the dependent variables for cross-sectional units, W is the spatial weight matrix, ρ is a scalar parameter, and ρWY denotes the interaction effects of the dependent variables Y at this location with the dependent variables of neighborhoods. X is a matrix of all explanatory variables containing different forms and β is a vector of fixed but unknown parameters. α is a scalar parameter and e represents an independently and identically distributed error term with zero means and variance σ^2.

An alternative model incorporates spatial dependence in the error term which is called spatial error model. It can be explained that the "errors associated with any one observation are a spatially weighted average of the errors at nearby sites plus a random error component" (Maddison, 2006). This is more commonly used because it is consistent with a situation where "determinants of the dependent variable omitted from the model are spatially autocorrelated, and with a situation where unobserved shock follow a spatial pattern" (Elhorst, 2011). The spatial error model in matrix form is given by

$$Y = \alpha + \beta X + e, \quad e = \lambda We + \mu \tag{2}$$

where λ is a scalar parameter called the spatial autocorrelation coefficient.

However, changes in dependent variables contribute to the spatial interactions in addition to the changes induced by the explanatory factors, therefore, LeSage and Pace (2009) recommend Spatial Durbin model in which the spatial lag model is augmented by the spatially weight value of independent variables. In our study, Spatial Durbin model can be formulated as,

$$\ln\boldsymbol{e_{it}} = \rho \sum_{j=1}^{N} \omega_{ij}\, e_{jt} + \alpha_i + \gamma_t + \beta_1 lny_{it} + \beta_2 (lny_{it})^2 + \beta_3 (lny_{it})^3 + \boldsymbol{Z_{it}\eta} + \lambda \sum_{j=1}^{N} \mathbf{x_{it}}\, \mu_{jt} + \boldsymbol{\varepsilon_{it}} \tag{3}$$

where $\boldsymbol{e_{it}}$ is CO_2 emissions per capita of province i at t year. Similarly, $\rho \sum_{j=1}^{N} \omega_{ij}\, e_{jt}$ denotes the average weighted effects of emissions from the neighboring provinces on emissions from province i. y_{it} is provincial per capita of GDP at 1978 constant price. Here we use the logarithm of GDP per capita at province level, its square and particularly cubic value as the explanatory variable because some recent studies have started to take it as a more precise way to posit an EKC relationship. $\boldsymbol{Z_{it}}$ represents all the control variables, in our study, population density and industry composition are included. $\lambda \sum_{j=1}^{N} \mathrm{x}_{\mathrm{it}}\, \mu_{jt}$ indicates the total interaction effects of national GDP per capita, population density and industry composition of province *i* along with those of the neighboring provinces on per-capita emissions from province i. Spatial Durbin model in effect can be simplified to either the spatial lag model or the spatial error model, which can be achieved by likelihood ratio (LR) test and Wald test. For theoretical derivation, please see (LeSage and Pace, 2009; Elhorst, 2012).

Neither form of spatial regressions can be estimated by the ordinary least squares (OLS) method which would result in spurious estimations of parameters. Specifically, for spatial lag model, the OLS estimator disables the property of being unbiased and consistency hold by the response parameters. When estimating specification includes the spatial error, the OLS estimator of the response parameters remains unbiased, though, it is not any more confirmed with the property of efficiency. Therefore, it is suggested to use a variety of techniques to overcome these difficulties, for example, the maximum likelihood (ML) in the earlier time (Anselin, 1988; Anselin and Hudak, 1992), and recently two nonparametric covariance estimation techniques specifically general methods of moments (GMM) (Lee, 2007) and instrumental variables (IV). However, estimation results might be partially inconsistent because of number of observations (*N*) and length (*T*). Lee and Yu (2010) proposed two methods to correct for this bias and obtain the consistent results. You can get detailed information from their technical manuscripts.

Elhorst (2003) pinned down three reasons why both types of above the models need to be considered. As both forms present its unique spatial extensions to the traditional panel data models, especially when "nonspatial model based on Lagrange multiplier (LM) or robust LM tests is rejected in favor of the spatial lag or the spatial error model, one should be careful to endorse one of these two models" (Elhorst, 2012). Generally, LM checks for a spatially lagged dependent variable and for spatial error autocorrelation, the robust LM tests check for a spatially lagged dependent variable in the local presence of spatial error autocorrelation and for spatial error autocorrelation in the local presence of a spatially lagged dependent variable (Elhorst, 2012). Therefore, theoretical reasoning along with diagnostic tests jointly works on the determination of which specification used in research. Figure 3 illustrates the framework of our research. To begin with, we conduct Moran'I test to check the spatial correlation between provinces and then we use Theil index to decompose the emissions inequality contributed by intra-regional as well as inter-regional effects. Next we impose LM as well as robust LM tests on the nonspatial models to identify the fixed effects forms whilst diagnose spatial relationships. Then, we impose Wald and LR tests on the spatial models obtained by the first step. After that we decompose the results from the perspective of direct, indirect and total effects. Finally we calculate the turning points for GDP per capita by means of spatial and nonspatial models and compare them from the perspectives of policy, regional assistance and industry transfer. These programs of the specifications identification are realized by Matlab and provided by Paul Elhorst at his website www.reroningen.nl/elhorst.

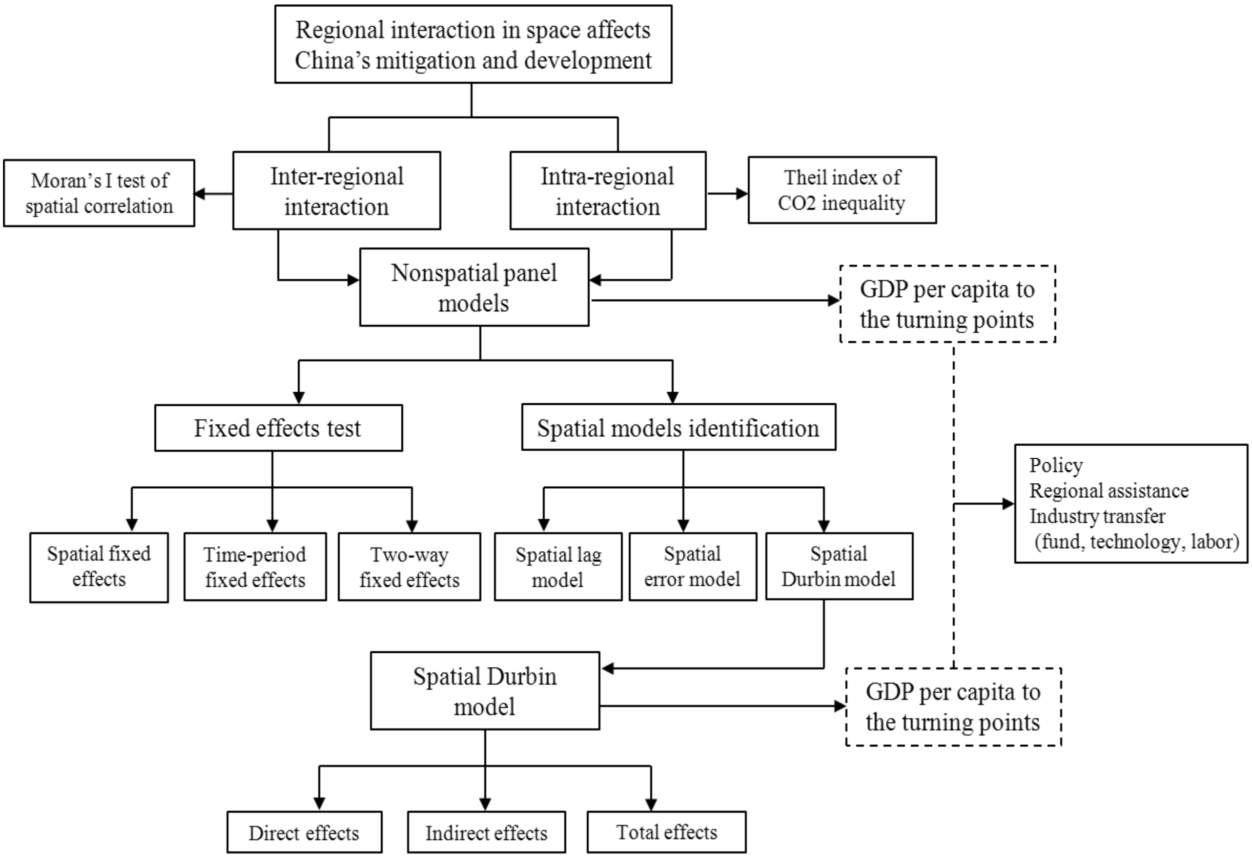

Fig. 3 Framework of study on how spatial interaction affects mitigation and development

In this study, the logarithm of provincial emissions is regressed on the logarithm of provincial GDP per capita as the explanatory variables, and population density as well as industry composition as the control variables. Initially, we have tried several different variables and finally single out the above group that measuring the environment and industrialization level of one particular province. Specifically, we calculate CO_2 emissions of 29 provinces[1] using the method proposed by Du (2010). The provincial data set of energy consumptions, GDP (1978 constant price), province area, population and added value by industry all comes from China Statistical Yearbook, China Energy Statistical Yearbook, Energy Balance Table, China Statistical Yearbook for Provinces, Comprehensive statistical data

[1] Data on Sichuan Province and Chongqing City is emerged; Xizang Autonomous Region is excluded due to data inaccessibility

and materials on 60 years of new China and other references. Then we emerge the data sets with a sum of 493 observations and obtain the per capita emissions measured by metric tons per person, the real GDP per capita measured at 1978 constant price, population density by persons per square kilometers and industry composition by percentage accordingly (see Table 1).

Table 1 Data descriptions

Variable	Definition	Unit	Mean	SD	Observations
CO_2 emissions per capita	Provincial per capita of fossil fuel induced CO_2 emissions	Metric tons per person	4.52	3.10	493
GDP per capita	Deflating provincial nominal GDP using the province specific deflators with 1978 as the base year	Yuan per person	4371.60	4070.39	493
Population density	The number of people per unit of area, usually quoted per square kilometer	Persons per square kilometers	402.33	536.70	493
Industry composition	Ratio of value added by industry over total value	%	37.31	8.36	493

The conventional EKC is augmented by the spatial weighted values, which indicates that how to construct the spatial matrix in a proper way becomes the key procedure. Given that some articles have elaborated on weighting methods (see Niebuhr and Annekatrin, 2000; Anselin, 2002; Garrett and Marsh, 2002; Madariaga and Poncet, 2007), this paper does not attempt to go over the basics. The most commonly used form is presented as the ROOK principle which indicates a contiguity matrix where $w_{ij}*=1$[2] if one region shares a common land border with another region, otherwise $w_{ij}*=0$. This nevertheless easily misses some information in the case that the Canada and Mexico who are patently connected nevertheless are unrelated because they do not share the same land border. Usually, the weight matrix is row standardized for rows sum to unity and elements of the leading diagonal are valued zeroes. Moreover, we use other two methods to construct the weight matrix and the estimation results corresponding to each method can be provided upon your request.

4. Results and analysis

This section will be followed by a series of test and regression results. The generalized Moran's test is firstly employed in order to see how regions cluster in terms of individual emissions, furthermore, to observe the spatial relationship before we formally decide to incorporate the spatially weight value into the model. And then the estimation results of nonspatial and spatial models are given and further analyzed. Next, total effects of explanatory variables on the provincial emissions are decomposed into direct and indirect

[2] w_{ij*} is an element of the unstandardized weight matrix, w_{ij} is an element of the standardized weight matrix.

effects with regard to the corresponding turning points. Finally we compare our results under three weighting methods.

4.1 Moran's *I* test of spatial autocorrelation

Moran's test is used to check for the spatial autocorrelation. The generalized Moran's *I* is measured within -1 to 1. If Moran's *I* falls into the interval of 0 to 1, it means that one location is neighboring places that have the same situation with it; otherwise, opposing relationship occur for one place against its neighbors. Moran scatter plot is divided into four quadrants and it is used to illustrate the spatial dependence in a clear way. Units that fall into the first and third quadrants represent that they have a positive correlations with its neighboring places, which are called HH area and LL area respectively. Units that fall into the second and fourth quadrants are those who have a negative correlation with its neighbors, which are called LH and HL area accordingly.

Table 2 Moran's *I* test of provincial per capita emissions from 1995 to 2011

Year	**Moran's *I***	**p-value**	**Year**	**Moran's I**	**p-value**
1995	0.2022	0.001	**2004**	0.1280	0.010
1996	0.1946	0.002	**2005**	0.1445	0.006
1997	0.2124	0.001	**2006**	0.1365	0.007
1998	0.1692	0.005	**2007**	0.1289	0.011
1999	0.1732	0.004	**2008**	0.1124	0.013
2000	0.1724	0.004	**2009**	0.0953	0.016
2001	0.1849	0.003	**2010**	0.0882	0.024
2002	0.1625	0.004	**2011**	0.0367	0.046
2003	0.1387	0.007			

Source: author's calculation

It can be easily seen that, regions cluster in general because Moran's *I* in all years are statistically significant. It means that province with high emissions is immediately neighboring one also with high emissions while province with low emissions is in close proximity to those of low emissions. It is obviously illustrated in Figure 4 that nine provinces are located in the HH quadrant and eleven provinces in the LL quadrant in 1995 while most provinces converge in the LH quadrant in 2011 This is in accordance with the situation where provinces clustering in the east area are in the fast pace of development followed by large amount of energy consumption while those in middle and west area have recently started to launch great projects of construction and even expansion. Imbalance of resource endowment among regions partly accounts for the spatial dependence in data as well. Interestingly, this spatial dependence has presented itself in a diminishing way, especially in 2011, decreased to 0.0367. This is probably as a consequence of less dependence of policies that specific to one province upon neighboring places. On the other hand, fierce competition on resource exploitation between regions would occur, especially after the announcement of the "Go West" campaign.

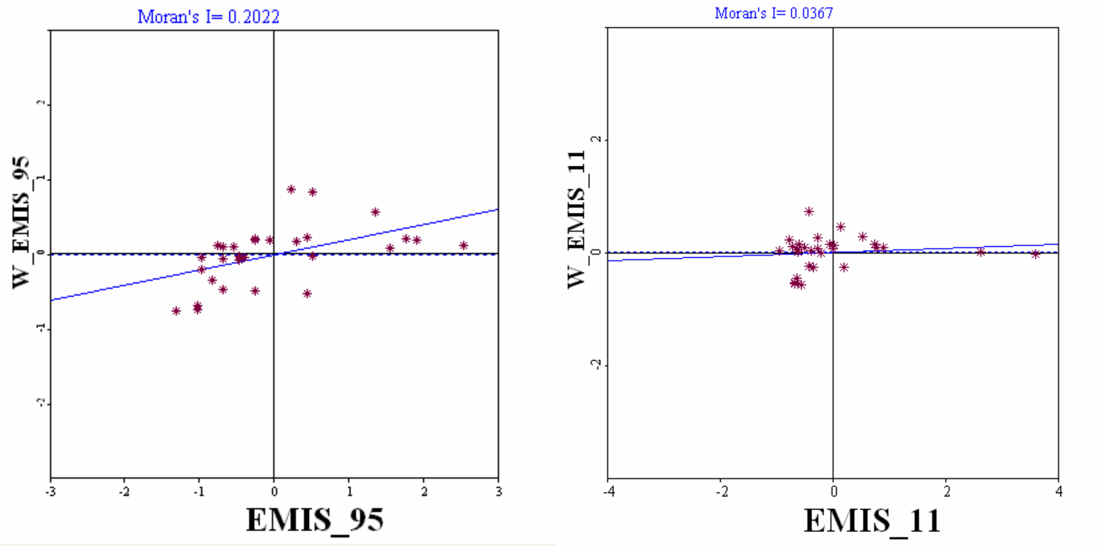

Fig. 4 Scatter plots of Moran's I in 1995 and 2011

4.2 Emissions inequality between the East, Northeast, Middle and West China by Theil index

Inequality in emissions occurred among regions as a result of differentiated developing stages and understanding the internal dynamics of carbon inequality within these regions has the potential to shape future mitigation policies (Clarke-Sather et.al, 2011). In this section, the regional carbon inequality is measured by Theil index which allows for the decomposition of inequality within regions as well as between regions. Theil index T_i in our study can be calculated as follows.

$$T_I = \sum_{i=1}^{N} \frac{E_i}{E_N} \times \log\left(\frac{E_i/E_N}{P_i/P_N}\right) \tag{4}$$

where E_i and P_i represent the total emissions and population of province i, while E_N and P_N represent the total emissions and population of all sample provinces.

Next, we decompose the Theil index into two parts, namely Theil within region (T_w) and between region (T_b), which is given as

$$T_I = T_w + T_b \tag{5}$$

Theil within region equals the contribution by intra-regional provinces to the inequality, which is given as,

$$T_w = \sum_{r=1}^{4} \frac{E_r}{E_N} \sum_{i_r=1}^{N} \frac{E_{i_r}}{E_r} \times \log\left(\frac{E_{i_r}/E_r}{P_{i_r}/P_r}\right) \tag{6}$$

where E_r and P_r are the total emissions and population of four regions that the East, Northeast, Middle and West China. i_r refers to those intra-regional sample provinces.

Theil between regions equals the inter-regional contribution to emission inequality, which is given as,

$$T_b = \sum_{r=1}^{4} \frac{E_r}{E_N} \times \log\left(\frac{E_r/E_N}{P_r/P_N}\right) \tag{7}$$

Here, we define that East China includes East China includes Municipality of Beijing, Municipality of Tianjin, Hebei Province, Municipality of Shanghai, Jiangsu Province, Zhejiang Province, Fujian Province, Shandong Province, Guangdong Province, Hainan Province; Northeast China includes Liaoning Province, Jilin Province and Heilongjiang Province; Middle China includes Shanxi Province, Anhui Province, Jiangxi Province, He'nan Province, Hubei Province, Hu'nan Province; West China includes Inner Mongolia, Guangxi Hui Autonomous Region, Sichuan Province, Municipality of Chongqing, Guizhou Province, Yun'nan Province, Shannxi Province, Gansu Province, Qinghai Province, Ningxia Province, Xinjiang Uygur Autonomous Region and Tibet. Given the data inaccessibility, we emerge the data sets of Sichuan and Chongqing, while Tibet is ignored.

Figure 5 illustrates that the inequality at the national scale levels off during the past 17 years. Differences in emissions between regions are narrowed whilst within region are expanded, which indicates that “convergence club” in a way is diminishing. Inequality of carbon emissions that contributed between regions only takes account for no more than 10 percent in 2011. It is not surprising because, for one thing, leading provinces in the eastern area undertake an average of 18 percent reduction of carbon intensity in the baseline of 2010, heavier than the other three regions; for another, as China has launched the “Go West” campaign since 1998, the western area is allowed to construct infrastructure for agricultural production, energy, transportation. Moreover, the western area also holds responsible for undertaking the industry transfer from other regions or even abroad, like manufacture, or ventures in agroindustry or mineral exploitation. In addition, the middle region, a bridge connecting the east and west area, is ready to be revitalized according to the national strategy. Actually, spillover induced by the spatial dependence often exerts stronger effects on places nearby and then gradually extended to outskirts. For instance, Shanghai has played a leading role in facilitating the neighboring cities like Hangzhou, Suzhou and Nanjing in a way of enhancing the tourism and attracting the investments. Nevertheless, the south part of Jiangsu is developed one step ahead of the north part thanks to being close to Shanghai and Zhejiang. Therefore, gap between regions will finally be diminishing by stage.

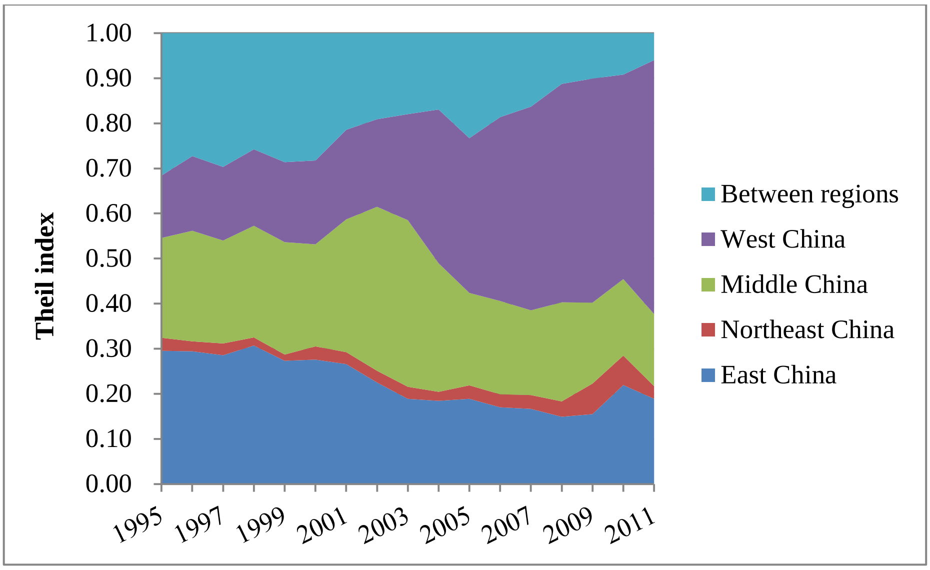

Fig. 5 Components of Theil index of carbon inequality

However, differences within regions are expanding due to the sharp increase of the contribution by Western China. The truth is intra-inequality of the other three regions is diminishing except the west area. In specific, the eastern region holds an average of 2.6 percent decrease in contributing to the nationwide emission inequality during the past 17 years and the middle region 1.9 percent. In fact, provinces in the east area have been clustering in small economic zone such as Beijing, Tianjin and some counties in Hebei as a group, while Pearl River Delta Economic Zone and the Yangtze River Delta Economic Zone are highly developed neck in neck, which can explain why provinces in the east area are slightly differentiated. Comparatively, as Chongqing, Sichuan and Guizhou are attracting more attention, components in the western area begin to highly differentiated, leading to an 8 percent increase of contribution to inequality. On the basis of all results, we find that whether convergence or divergence within region or between regions would make a difference in China's action, thus, we decide to take the spatial dependence into account in our study.

4.3 Estimation results of nonspatial and Spatial Durbin models

1) Results of nonspatial models

Here we construct a model selection framework according to the estimation results. Table 3 can be interpreted in following aspects.

Table 3 Estimation results of CKC models by OLS (pooled OLS), spatial fixed effects, time-period effects, spatial and time-period effects

Determinants	(1) Pooled OLS	(2) Spatial fixed effects	(3) Time-period fixed effects	(4) Spatial and time-period fixed effects
Intercept	40.731*** (3.261)			
lny	-13.021*** (-2.852)	-6.615*** (-2.784)	-6.386 (-1.420)	-3.333* (-1.733)
$(\text{lny})^2$	1.659*** (2.998)	0.954*** (3.278)	0.840 (1.542)	0.688*** (2.928)
$(\text{lny})^3$	-0.066*** (-2.983)	-0.040*** (-3.409)	-0.034 (-1.536)	-0.033*** (-3.493)
lnpop	-0.197*** (-11.800)	-0.200 (-1.148)	-0.1614*** (-9.562)	0.915*** (4.021)
indadd	0.012*** (5.602)	0.015*** (7.122)	0.014*** (6.588)	0.013*** (7.421)
R^2	0.657	0.947	0.688	0.966
σ^2	0.127	0.020	0.115	0.013
logL	-187.674	270.842	-164.391	379.389
D-W	1.941	1.284	2.042	1.890
LM spatial lag	118.403***	47.800***	74.613***	7.130***
LM spatial error	93.203***	73.751***	72.076**	0.621
Robust LM spatial lag	28.409***	0.057	6.366**	13.171**
Robust LM spatial error	10.412*	26.008***	3.828**	6.662***
LR-test joint significance spatial fixed effects		1087.561***	(p=0.000)	
LR-test joint significance time-period fixed effects		217.095***	(p=0.000)	

Note: 1) t-values in parentheses 2)*, **, and *** indicate that the coefficient is significantly different from zero at the 10%, 5% and 1% significance level, respectively. 3) lny is the logarithm of provincial GDP per capita, lnpop is the logarithm of population density and indadd refers to industry composition; logL means the logarithm of likelihood, the larger it is, the better performance.

It appears that the spatial and time-period fixed effects model (also known as two-way fixed effects) has a relatively good performance compared with the other three models, because the largest R-square, the largest logL and the least variance all fall into this model. Additionally, D-W around 1.9 shows little evidence of autocorrelation. The results of LR tests (1087.561, with 29 degrees of freedom) shows little possibility that the spatial fixed effects are jointly insignificant. Similarly, the hypothesis that the spatial fixed effects as well as the time-period fixed effects being jointly insignificant is also rejected according to the LR test results (1087.561 with 29 degrees of freedom and 217.095 with 27 degrees of freedom). Among the four models, by both LM test and Robust LM test, the hypothesis of either no spatially lagged dependent variable or no spatially autocorrelated error term is mostly rejected at 10 percent, 5 percent as well as 1 percent significance, which provides the evidence of employing Spatial Durbin model as the specification.

2) Results of Spatial Durbin model

Next, we spell out some tests that incorporate spatial effects into the regression model. According to Table 4, Column 1 reports the results of nonspatial model with spatial and time-period fixed effects, while Column 2 and 3 are results of Spatial Durbin model without/with bias correction. Compared with the coefficient estimation using direct approach, differences are slight when bias is corrected; yet, the coefficient of the spatial lagged dependent variables ($W*lnCO_2$) seems to be more sensitive to the corrected model. Generally, $W*lnCO_2$ is negative, which means regions compete for the emission rights from the nationwide perspective. This is reasonable as currently the conventional resources like coal and oil are still competitive in China, provinces in the middle and west China are challenged with the worsened environment and low capability, leading to the fact that most regions with low emissions are, in a way, deprived of chances to exploit the resources that are expected for further development.

The spatially lagged value of the independent variables presents itself in a way to observe how neighbors affect the local province. In particular, it can be seen in Table 4 that the coefficients of the spatial lagged population density are negative, which means that more residence in the neighboring provinces might result in the reduction of local carbon emissions. Similarly, industry in the neighborhood expands also allows for mitigation in the local region. It seems reasonable that emissions in the local region might decrease to a degree because more energy would be exploited in order to meet the growing demand by the neighbors induced by the extension of population and heavy industry.

However, the estimation of the coefficients by is not invalid for any comparison or calculation of turning points, because they do not, like in a nonspatial model, represent the marginal effect of a change in the income or any other explanatory variables on carbon emissions. Here, the total effects of the income change on emissions are composed into direct and indirect effects. Table 4 lists all the results of a. model of the spatial and time-period fixed effects (two-way fixed effects) without spatial connections (See Model (1)); b. the coefficient estimates of all variables in the Spatial Durbin model of two-way fixed effects without/with bias correction (See Model (2) and (3)); c. the direct, indirect and total effects of the Spatial Durbin model of two-way fixed effects without/with bias correction (See Model (4) and (5)).

Secondly, the reason why the income elasticity -4.696 in Model (2) is different from the direct effects -4.727 in Model (4) is due to the feedback effects. The feedback effects, measured at 0.031, arise as a consequence of a two-way interaction that carbon emissions change as the economy of one particular area grows, impacts of local emissions changes then pass through neighbors in a successive way and finally back to the local area itself (Elhorst, 2012). Both the spatially lagged independent variables, along with the spatially lagged dependent variable, account for the feedback effects, which inevitably happened yet cannot be visually seen. Nevertheless they are quite small in light of population density and industrial composition.

Thirdly, the indirect effects tempt to measure the effects of per capita income and other factors on the carbon emissions of neighboring provinces and then back to the particular province, which are obvious but statistically insignificant. The indirect effects account for approximately 60 percent of the direct effects in case of the provincial per-capita income, in other words, if the local income changes, the change of neighboring provinces to the change of local province is in the proportion of more than 1 to 1.65. In view of population density and industrial composition, the direct effects are somewhat offset by the indirect effects. Therefore, only by adding direct and indirect effects together, can the real contribution be revealed when spatial relationship is included in models.

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Table 4 Results of the non-spatial model and the Spatial Durbin model in direct, indirect and total effects

	Nonspatial models	**Spatial Durbin model**								
	Two-way fixed effects	**Two-way fixed effects**	**Two-way fixed effects (bias-corrected)**	**Two-way fixed effects**			**Two-way fixed effects (bias-corrected)**			
Effects	--	Coefficient estimate	Coefficient estimate	Direct	Indirect	Total	Direct	Indirect	Total
lny	-3.333* (-1.733)	-4.696* (-2.198)	-4.664* (-2.080)	-4.727** (-2.191)	-2.851 (-0.665)	-7.578* (-1.970)	-4.629** (-2.050)	-3.307 (-0.702)	-7.936* (-1.797)
$(lny)^2$	0.688*** (2.928)	0.843*** (3.2333)	0.840*** (3.072)	0.849*** (3.200)	0.249 (0.477)	1.098** (2.398)	0.836*** (3.034)	0.305 (0.533)	1.141** (2.172)
$(lny)^3$	-0.033*** (-3.493)	-0.040*** (-3.760)	-0.040*** (-3.576)	-0.040*** (-3.704)	-0.009 (-0.409)	-0.049** (-2.619)	-0.040*** (-3.533)	-0.011 (-0.471)	-0.051** (-2.367)
lnpop	0.915*** (4.021)	0.689*** (2.940)	0.692*** (2.814)	0.688*** (2.959)	-0.273 (-0.589)	0.415 (0.812)	0.687** (2.750)	-0.250 (-0.481)	0.437 (0.768)
indadd	0.013*** (7.421)	0.012*** (6.795)	0.012*** (6.519)	0.012*** (6.991)	-0.005 (-1.328)	0.007* (1.892)	0.012*** (6.501)	-0.005 (-1.245)	0.007 (1.660)
W*lnCO_2	--	-0.076 (-1.252)	-0.017 (-0.280)	--	--	--	--	--	--
W*lny	--	-3.356 (-0.752)	-3.129 (-0.669)	--	--	--	--	--	--
W*$(lny)^2$	--	0.330 (0.609)	0.287 (0.506)	--	--	--	--	--	--
W*$(lny)^3$	--	-0.012 (-0.562)	-0.010 (-0.447)	--	--	--	--	--	--
W*lnpop	--	-0.200 (-0.396)	-0.242 (-0.457)	--	--	--	--	--	--
W*indadd	--	-0.004 (-1.055)	-0.005 (-1.145)	--	--	--	--	--	--

Note: 1) t-values in parentheses 2)*, **, and *** indicate that the coefficient is significantly different from zero at the 10%, 5% and 1% significance level, respectively.

4.4 Results comparison within different models

Next, we calculate the nationwide GDP per capita that corresponding to the turning points in each non-spatial and Spatial Durbin model (SDM).

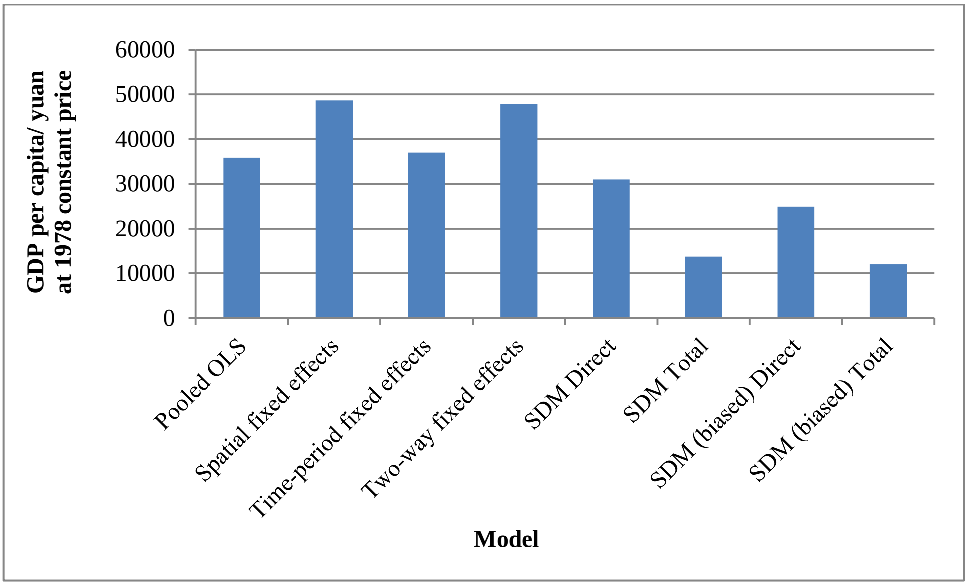

Fig. 6 Turning points of GDP per capita in nonspatial models and SDM models

Source: authors' calculation

Figure 6 overall illustrates that the turning points corresponding to the nonspatial models are much higher than their counterparts in the spatial panel models. More specifically, the nonspatial models of spatial fixed effects generates the largest real GDP per capita which amounts to 487634.8 yuan (1978 constant price), while the biased corrected Spatial Durbin model has the smallest above the total effects. This implies that the consideration of spatial connections naturally makes it easier for regions to achieve peak emissions. In addition, the reason why results over the direct effects are nearly twice as those over the total effects is that emissions and income are interactively affected not only by regions who share the same border (first-order neighbors) but cities or provinces who neighboring the first-order neighbors. In fact, if one particular province decides to implement a local policy, it might benefit more since its neighbors have in turn facilitate the local area itself; or the policy might fail as profits are unexpectedly taken away by its neighbors. The eastern region has exported carbon emissions to the middle and west when it is ready transfers the heavy industry outside (Liu et al, 2010). Sooner or later, spillover of mitigation by the East China will in turn be extended to the other regions in a way of investment encouragement, technology diffusion, and labor migration. Obviously, spatial interaction acts actively in promoting the mitigation plan and reaching emissions peak at the expense of lower income. In other words, it seems necessary to pay more attention to those leading area and fairly important to consider the spatial dependence when design mitigation policy.

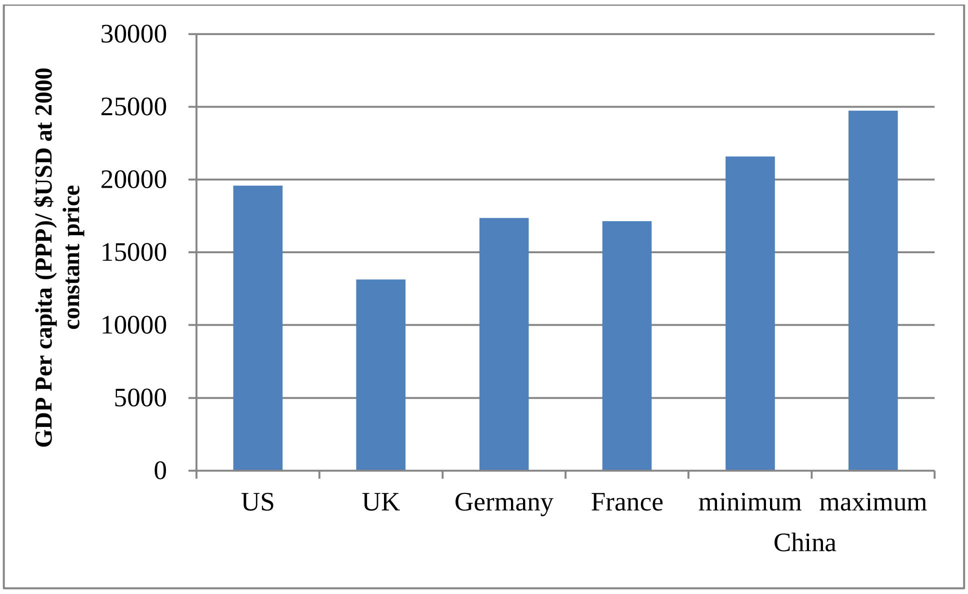

Fig. 7 Turning points of GDP per capita (PPP) of the US, the UK, Germany, France and China

If compared from a global perspective, China will reach the peak emissions at a higher individual income (see Figure 7). The turning point in the United Kingdom occurred in 1971 at approximately USD 13000 GDP per capita (2000 constant price), the United States in 1973 at USD 19500, Germany and France in 1979 around USD 17000. It appears that most of the developed countries have passed the stage where industrialization and urbanization triggered by large energy consumption, and now they are looking for clean patterns, like the reform that energy consumption transfers from petroleum to shale gas commences in the United States and the strict and comprehensive regulations on renewable energy are proposed by the Europe Union, all enable them a low-carbon economy in the future whilst shows China a good example of how to design the roadmap for sustainability patterns .

In recent years, China has been working on emissions reduction. Provinces are allocated with a specific mitigation target and China has achieved a totally 19 percent of energy intensity reduction during the Eleventh Five-Year Plan. Also, the government has started to pay more attention to the renewable energy, in a hope to achieve clean and sustainable patterns of energy consumption. In all words, the essence of improving efficiency falls into the utility of renewable energy, however, large amount of investment in China is needed not only for the basic demand for survival, but also to fulfill the demands for R&D as well as marketization on advanced technologies and equipment, to subsidize those who are encouraged to use clean products or even supporting those who lost jobs because the heavy-pollutant industries they worked for are discarded. In this way, it seems that if without any assistance from other industrial countries, China would get to the peak emissions at a relatively higher price.

5. Conclusion

Spatial dependence, as it undoubtedly exists in real life, yet has been long neglected when models are estimated. It is more likely to “risk misspecification and are in danger of presenting a deceitful story of the reasons why emissions change over time” when researchers forget to take the spatial effects into their models (Maddison, 2006).

By conducting Moran’ I test, we find that from a nationwide perspective, carbon emissions patterns are similar when regions cluster, but this locally regional dependence is diminishing by year. The decomposed Theil index tells the reason that inequality in emissions contributed by inter-regional differences is decreasing by 9 percent since 1995. Faced with the heavier mitigation targets, the eastern region has to make a compromise to the competition by the revitalization in Middle China and great leap in West China. The truth is gap within the west part has made increasing contribution with an average growth rate of 8 percent to the emissions inequality, in sharp contrast to the other three regions. It appears that regional interaction in space might have been becoming more complicated and thus, increasingly important to China’s mitigation action and social development in the future.

We then employ one specific form of the spatial panel models, Spatial Durbin model, to shape the relationship between mitigation and economic growth using the panel data of 29 provinces ranging from 1995 to 2011. On the basis of all results, it is more likely that peak emissions occur when the GDP per capita reaches between $USD 21594 to 24737 at 2000 constant price. It seems much lower when compared with the estimations of models which ignore the spatial dependence, but still higher than some highly industrialized countries who have passed the emissions peak. In fact, provinces often mimicking other favorable environmental policies in order to reduce the costs in decision-making, especially those policies implemented by regions where share the similar resource, preference and development patterns. For China, the effects of policies of updating industries, advancing technologies and adjusting consumption structures would be largely strengthened by fully taking advantage of the regional interactions.

Reference

Aldy, J. E. (2005). "An Environmental Kuznets Curve Analysis of U.S. State-Level Carbon Dioxide Emissions." *The Journal of Environment and Development*, **14**(1): 48-72.

Anselin, L. (1988). Spatial Econometrics: Methods and Models. Kluwer Academic, The Netherlands.

Anselin, L., and Hudak, S. (1992). Spatial econometrics in practice: A review of software options. *Regional science and urban economics*, **22**(3), 509-536.

Anselin, L. (2010). Thirty years of spatial econometrics. *Papers in Regional Science*, **89**(1), 3-25.

Anselin, L. (2002). Under the hood issues in the specification and interpretation of spatial regression models. *Agricultural economics*, **27**(3), 247-267.

Auffhammer, M. and R. T. Carson (2008). Forecasting the path of China's CO_2 emissions using province-level information. *Journal of Environmental Economics and Management*, **55**(3): 229-247.

Baltagi, B., Song, S.H. and Koh, W. (2003). Testing panel data regression models with spatial error correlation. *Journal of Econometrics*, **117**(1): 123-150.

Baltagi, B., Egger, P. and Pfaffermayr, M. (2007). A generalized spatial panel data model with random effects. Working Paper, Syracuse University.

National Bureau of Statistics of China (NBSC-a), 1991-2012. China Energy Statistical Yearbook. China Statistics Press, Beijing in Chinese.

National Bureau of Statistics of China (NBSC-b), 1991–2012. China Statistical Yearbook. China Statistics Press, Beijing in Chinese.

Clarke-Sather, A., Qu, J.S., Wang, Q., Zeng, J.J. and Li, Y. (2011). Carbon inequality at the sub-national scale: A case study of provincial-scale inequality in CO_2 emissions in China 1997-2007. *Energy Policy*, **39**(9), 5420-5428

Department of Comprehensive Statistics of National Bureau of Statistics (1999). Comprehensive statistical data and materials on 60 years of new China. Peking: China Statistics Press.

Dijkgraaf, E. and Vollebergh, H. R. J. (2005). A Test for Parameter Homogeneity in CO_2 Panel EKC Estimations." *Environmental and Resource Economics*, **32**(2): 229-239.

Du, L.M. (2009). Impact Factors of China's Carbon Dioxide Emissions: Provinceial Panel Data Analysis. *Journal of South Economics*, **11**: 20-33.

Elhorst, J.P. (2003). Specification and estimation of spatial panel data models. *International Regional Science Review*, **26**(3): 244-268.

Elhorst, J.P. (2012). Matlab Software for Spatial Panels. I*nternational Regional Science Review* 0160017612452429.

Elhorst, J.P., Lacombe, D. J., and Piras, G. (2012). On model specification and parameter space definitions in higher order spatial econometric models. *Regional Science and Urban Economics*, **42**(1), 211-220.

Elhorst, J.P. (2014). Spatial panel data models. Working paper. In *Spatial Econometrics* (pp. 37-93). Springer Berlin Heidelberg.

Fu, J.F., Gu, Q.X., and Shi, H.D. (2008). Empirical Study on the CO2 Environmental Kuznets Curve based on Production- and Consumption-based CO2 emissions. *Advances in Climate Changes Redearch*, **4**(6): 376-381.

Garrett, T.A., and Marsh, T.L. (2002). The revenue impacts of cross-border lottery shopping in the presence of spatial autocorrelation. *Regional Science and Urban Economics*, **32**(4), 501-519.

Grossman, G.M., and Krueger, A. B. (1991). Environmental impacts of a North American free trade agreement (No. w3914). National Bureau of Economic Research.

Han, Y.J. and Lu., Y. (2009). The Relationship Between Economic Growth and Environmental Quality: An Empirical Test on the Environmental Kuznets Curve of CO_2. *Journal of Economic Review and Management*, 3:3-11.

Heston, A., Summers, R. and Aten, B. (2009). Penn World Table Version 6.3, Center for International Comparisons of Production, Income and Prices at the University of Pennsylvania.

Kapoor, M., Kelejian, H.H. and Prucha, I.R. (2007). Panel data models with spatially correlated error components. *Journal of Econometrics*, **140**: 97-130.

Madariaga, N. and Poncet, S. (2007). FDI in Chinese cities: Spillovers and impact on growth. *The World Economy*, **30**(5), 837-862.

Niebuhr, A. (2000). *Convergence and the effects of spatial interaction* (No. 110). HWWA Discussion Paper.

Lee, L.F. (2007). GMM and 2SLS estimation of mixed regressive, spatial autoregressive models. *Journal of Econometrics*, **137**(2): 489-514.

Lee, L.F. and Yu, J. (2010). Estimation of spatial autoregressive panel data models with fixed effects. *Journal of Econometrics*, **154**(2): 165-185.

Lee, L.F. and Yu, J. (2010). Some recent developments in spatial panel data models. *Regional Science and Urban Economics*, **40**(5): 255-271.

LeSage, J. and Pace, R. K. (2008). *Introduction to spatial econometrics*. CRC press.

Liu, H.G., Liu, W.D., Tang, Z.P. and Fan, X.M. The Effect Analysis of Regional Industry Structure Adjustment for CO_2 Emission reduction in China: On the Base of Inter-regional Input-Output Method. *Areal Research and Development*, **29**(3): 129-135.

Maddison, D. (2006). Environmental Kuznets curves: A spatial econometric approach. *Journal of Environmental Economics and Management*, **51**(2): 218-230.

Richmond, A. K. and R. K. Kaufmann (2006). Is there a turning point in the relationship between income and energy use and/or carbon emissions? *Ecological Economics*, **56**(2): 176-189.

Schmalensee, R., Stoker, T. M., and Judson, R. A. (1998). World carbon dioxide emissions: 1950–2050. *Review of Economics and Statistics*, **80**(1), 15-27.

TheState Council of the People's Republic of China (SCPRC), 2011. The 12th Five-Year Plan Outline of National Economy and Social Developmen to the People's Republic ofChina. Availableat /http://news.xinhuanet.com/politics/2011-03/ 16/c_121193916.htmS (in Chinese).

Wang, C.J. (2009). Functio Simulation and Regularity of Distance Decay of Inter-Urban Traffic Flow in China. *Progress In Geography*, **28**(5), 690-696.

Wei Y.M., Wang, L., Liao, H., Wang, K., Murty, T and Yan J.Y. (2013). Responsibility Accounting in Carbon Allocation: A Global Perspective. Working paper.

Xu, G.Y. and Song, D.Y. (2010). An Empirical Study of the Environmental Kuznets Curve for China's Carbon Emissions—Based on Provincial Panel DataChina *Industrial Economics*, 5:

37-47.

Yu, J., de Jong, R. and Lee, L.F. (2008). Quasi-maximum likelihood estimators for spatial dynamic panel data with fixed effects when both n and T are large. *Journal of Econometrics*, **146**: 118-134.

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